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Fault detection for discrete-time Lipschitz nonlinear systems with signal-to-noise ratio constrained channels

Fumin Guo^a, Xuemei Ren^{a,*}, Zhijun Li^b, Cunwu Han^b

^a School of Automation, Beijing Institute of Technology, Beijing 100081, China

^b The Key Lab of Fieldbus and Automation Technology of Beijing, North China University of Technology, Beijing 100144, China

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ABSTRACT

In this paper, the problem of fault detection for discrete-time Lipschitz nonlinear systems with additive white Gaussian noise channels subject to signal-to-noise ratio constraints is investigated. An optimal residual generator based on the mixed H_{-}/H_{∞} performance index is designed to generate the so-called residual signal, and the H_{-} -index is used to measure the minimum effect of faults on the residual signal, while the influence of unknown disturbances and channel noise on the residual signal is maximized by the means of the H_{∞} -index. Then, in order to detect the occurrence of faults, a norm-based residual evaluation function is provided, and a dynamic threshold including upper bounds on the modulus of the solution of Lipschitz nonlinear systems and the stochastic properties of channel noise is also constructed. Finally, a simulated example is presented to demonstrate the effectiveness of the proposed approach.

1. Introduction

Due to the ever-increasing demands for higher safety and reliability of modern complex systems, in recent years, fault detection (FD) has attracted considerable research attention. In general, FD techniques can be classified into data-driven multivariate statistical process monitoring (MSPM) and model-based approaches. Because of less requirements on the design and simple forms, the data-driven MSPM methods, such as principle component analysis (PCA) and partial least squares (PLS), are widely used in large-scale industrial processes [1,2]. With the increasing complication of operation conditions and control objectives, nowadays the complicated dynamical multimode process has become a research focus, and some advanced MSPM approaches have been developed for the process; for example, the work in [3] proposed a new model migration method for the multimode non-Gaussian batch processes, and the common and specific variations were separated for the multimode problems. In addition, a novel manifold learning method was presented in [4] for the analysis of multimode batches in electro-fused magnesia furnace, and the proposed method showed superior monitoring and FD ability. More results of this research line can be found in [5,6].

* Corresponding author. E-mail address: xmren@bit.edu.cn (X. Ren).

http://dx.doi.org/10.1016/j.neucom.2016.02.048 0925-2312/© 2016 Elsevier B.V. All rights reserved. Compared with the data-based MSPM techniques, the modelbased FD methods can be successfully applied in the framework of modern control theory if the mathematical and physical knowledge of industrial processes are available. The core of model-based FD schemes is to detect the fault from the presence of unknown inputs on the basis of mathematical models, and the observer-based approach is the common one in these schemes. Generally, a typical observer-based FD system consists of a residual generator and a residual evaluator. The purpose of the residual generator is to produce a so-called residual signal, and then the generated residual signal is compared with a predefined threshold in the residual evaluator stage. A fault will be detected and an alarm will be released when the residual signal value exceeds the threshold [7–9].

Lipschitz nonlinear systems contain a large range of nonlinear systems, and any nonlinear functions whose arguments are smooth can be transformed into Lipschitz nonlinear [10–15]. Recently, some scholars have worked on FD for Lipschitz nonlinear systems and received some results. For a class of switched Lipschitz nonlinear systems with asynchronous switching surface, a FD filter was designed in [16] by using the average dwell time approach. Based on the results of [16], the authors in [17] further discussed FD for uncertain switched Lipschitz nonlinear systems, and a new hybrid FD filter with state update was constructed. Moreover, the works in [18,19] used different approaches to investigate the FD problem for uncertain Lipschitz nonlinear systems, and a novel observer-based FD method based on adaptive estimation techniques was presented in [18], while two nonlinear







observer design strategies, i.e., Thau's observer and sliding-mode observer, were proposed in [19]. In addition, reference [20] designed a nonlinear neural network FD observer to detect the fault for the non-Gaussian non-linear stochastic systems.

On the other hand, with the widespread application of network and communication technology, the merger between control and information theory has received more and more attention [21]. When networked communication channels take place in feedback control systems, the systems are inevitably subject to some constraints, such as transmission data rate, power (or variance) constraints, or signal-to-noise ratio (SNR) constraints, so one line of research proposes a framework to study stability of feedback control systems with SNR constraints. As the first step in the study of SNR constrained control systems, [22] investigated stabilization of multiple feedback systems subject to SNR constrained channels, and a minimal SNR was obtained in the discrete-time case for static feedback controllers to stabilize an unstable plant. However, [22] did not provide the robustness performance guarantee. Then, the authors in [23] considered the robustness related issue, and a closed-form characterization of SNR was achieved to satisfy the required robustness. In addition, the work in [24] investigated the required SNR for stabilization of linear invariant time (LTI) systems with additive colored Gaussian noise (ACGN) channels subject to channel input quantization, and two different infimum of SNR were gained for the logarithmic and uniform quantization. More research results can be found in [25-27].

It should be noticed that all the aforementioned Lipschitz results [16-20] were obtained in the continuous-time cases, and little attention has been paid to FD for discrete-time Lipschitz nonlinear systems. Furthermore, to the best of the authors' knowledge, most of the existing works on SNR constraints have considered merely the stabilization or performance issues, and no results have been obtained on FD for Lipschitz nonlinear systems with SNR constraints. Under this motivation, this paper investigates the problem of FD for discrete-time Lipschitz nonlinear systems subject to SNR constrained channels. Our aim is to design an FD filter to determine whether faults occur within the discretetime nonlinear system. Since noise and disturbances may lead to significant changes in the residual, FD filters have to remain robust for the purpose of escaping from false alarms [8]. Different from the concept in robust control, the robustness of an FD system includes not only robustness against disturbances and channel noise but also sensitivity to the possible faults, i.e., the designed FD system ought to guarantee a suitable compromise between sensitivity to faults and robustness against noise and disturbances. Thus, an optimal residual generator is constructed in the mixed H_{-}/H_{∞} framework to achieve the compromise; then, in order to detect faults, a norm-based residual evaluation function and a dynamic threshold based on the modulus of the solution of Lipschitz nonlinear systems and the stochastic properties of channel noise are designed.

The remainder of the paper is organized as follows: Section 2 introduces system model and some assumptions. Section 3 discusses the design procedures of an optimal residual generator and a residual evaluator which includes a residual evaluation function and a dynamic threshold. A simulation example and a conclusion are presented in Sections 4 and 5, respectively.

2. System model and assumptions

Consider the feedback control system with additive white Gaussian noise (AWGN) channels subject to SNR constraints shown in Fig. 1. The discrete-time Lipschitz nonlinear system can be described as:

$$\begin{aligned} x(k+1) &= Ax(k) + \varphi(x(k), u(k)) + Bu(k) + E_d d(k) + E_f f(k) \\ y(k) &= Cx(k) + F_d d(k) + F_f f(k) \end{aligned}$$
(1)

where $x(k) \in \mathbb{R}^n$ is the state vector, $y(k) \in \mathbb{R}^m$ is the plant output, $u(k) \in \mathbb{R}^p$ is the plant input, $d(k) \in \mathbb{R}^{n_d}$ denotes the unknown disturbance, and $f(k) \in \mathbb{R}^{n_f}$ is the fault to be detected. *A*, *B*, *C*, *E*_d, *E*_f, *F*_d, and *F*_f are known matrices with appropriate dimensions. In addition, the following assumptions should be made throughout the paper:

- (1) The pair (A, C) is detectable.
- (2) The nonlinear function $\varphi(x(k), u(k))$ is assumed to be a known nonlinear function satisfying the following local Lipschitz condition on a set $M \subset \mathbb{R}^n$ with respect to x:

 $\|\varphi(x_1, u(k)) - \varphi(x_2, u(k))\| \le \gamma \|x_1 - x_2\|, \quad \forall x_1, x_2 \in \mathbf{M}$ (2)

where $\gamma > 0$ is a Lipschitz constant.

Remark 1. If $M = R^n$, the nonlinear $\varphi(x, u)$ is said to be globally Lipschitz. Lipschitz systems constitute a very important class; for example, the sinusoidal terms encountered in robotics are usually termed as globally Lipschitz, while the square or cubic nonlinearities in nature are regarded as locally Lipschitz [28].

(3) Each system output is transmitted to the FD filter through an AWGN channel, i.e., $w_i = y_i + n_i$, where n_i is independent of y_i and is a zero mean Gaussian white noise sequence with variance $\sigma_{n_i}^2 (0 < \sigma_{n_i}^2 < \infty)$. Moreover, each AWGN channel is subject to SNR constraint [29]:

$$\frac{\sigma_{y_i}^2}{\sigma_{n_i}^2} = S_i, \quad i = 1, ..., m \tag{3}$$

where S_i is SNR of the *i*th channel, and $\sigma_{y_i}^2$ is the stationary variance of the *i*th channel input y_i . From [29], it can be seen that $\sigma_{n_i}^2$ is not a given constant and is proportional to $\sigma_{y_i}^2$.

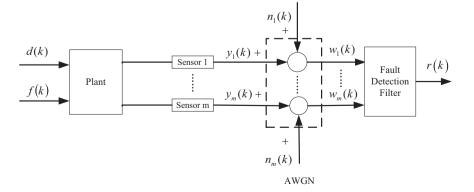


Fig. 1. Fault detection for the Lipschitz nonlinear systems subject to SNR constrained channels.

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