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Research Article

Distributed Fault Detection for a Class of Nonlinear Stochastic Systems

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A novel distributed fault detection strategy for a class of nonlinear stochastic systems is presented. Different from the existing design procedures for fault detection, a novel fault detection observer, which consists of a nonlinear fault detection filter and a consensus filter, is proposed to detect the nonlinear stochastic systems faults. Firstly, the outputs of the nonlinear stochastic systems act as inputs of a consensus filter. Secondly, a nonlinear fault detection filter is constructed to provide estimation of unmeasurable system states and residual signals using outputs of the consensus filter. Stability analysis of the consensus filter is rigorously investigated. Meanwhile, the design procedures of the nonlinear fault detection filter are given in terms of linear matrix inequalities (LMIs). Taking the influence of the system stochastic noises into consideration, an outstanding feature of the proposed scheme is that false alarms can be reduced dramatically. Finally, simulation results are provided to show the feasibility and effectiveness of the proposed fault detection approach.

1. Introduction

In recent years, with the increasing complexity of modern dynamic systems, more and more researchers are now investigating new fault detection and identification (FDI) schemes to ensure safety and reliability of these modern complex dynamic systems. Effective FDI schemes can help find the early indication of system faults and avoid breakdowns of these complicated plants. The model-based analytical redundancy approaches have been proved to be an effective way to detect and diagnose faults for linear systems in the last two decades [1, 2].

However, in many practical applications, a large number of dynamic systems are inherently nonlinear systems with some uncertainty, which include the transformer, some chemical processes, and robotic manipulators with homonymic constraints. There are fruitful research results on fault diagnosis schemes for nonlinear systems in recent years. In [3], Donghua and Yinzhong proposed a novel FDI scheme for a class of nonlinear systems. Strong tracking filter was employed for parameter estimation to achieve fault detection. Fault estimation and accommodation scheme for nonlinear time-delay systems was developed using adaptive fault diagnosis observer in literature [4]. A novel fast adaptive fault estimation algorithm was proposed to improve the accuracy of fault estimation. The existence of the proposed adaptive fault diagnosis observer was given in terms of matrix inequality. More recently, by combining adaptive learning control theory with neural network, Polycarpou et al. in [5–8] proposed an online learning approximator to detect and isolate system faults. These approaches were based on generic function approximator with adjustable parameters. In [7], Zhang et al. developed a sensor fault isolation scheme for a class of nonlinear systems using online learning approximator. In the presence of modeling uncertainties, Vemuri used adaptive techniques to estimate an unknown sensor bias for a class of nonlinear discrete-time systems. The robustness, sensitivity, and stability properties were rigorously investigated [8]. Chen and Saif in [9] proposed an iterative learning observer (ILO) based fault diagnosis approach for fault detection, identification, and accommodation. The states of the ILO were updated using the previous output errors and the control input vectors.

Due to the existence of some Gaussian or non-Gaussian noises, fault detection and identification for nonlinear stochastic systems are always challenging tasks [10–12]. There are fewer research results on FDI for nonlinear stochastic systems compared with fruitful research results for linear systems. An effective FDI method for linear stochastic systems is to apply Kalman filters or extended Kalman filters. For nonlinear stochastic systems, this situation turns to be much more complicated. Zhang et al. investigated a fault detection and isolation scheme for a class of Lipschitz nonlinear systems with nonlinear and unstructured modeling uncertainty using adaptive estimation techniques [10]. The fault detection and isolation scheme was composed of a fault detection estimator and a bank of fault isolation estimators. The fault detectability and isolability were also rigorously investigated. For fault isolation problems, Guo and Wang proposed a novel fault isolation scheme for nonlinear non-Gaussian stochastic systems with multiple faults [11]. In this work, the fault isolation problem was converted into an entropy optimization problem using a state estimator. By building output probability density functions (PDFs) of the stochastic error, a novel data-driven fault isolation algorithm was derived. For those unmeasurable system outputs, square root B-spline expansion approach was applied to find the relationship of entropy of the system outputs with system faults and noises [12].

The main difficulty of designing an effective fault detection observer is the influence of stochastic noises on residual signals, which can give rise to false alarm and reduce the accuracy of fault detection. In this paper, we present a novel distributed fault detection scheme for a class of nonlinear stochastic systems. The objective of the fault detection scheme is to minimize the influence of system stochastic noises on residual signals using parameter optimization techniques. Firstly, by constructing a consensus filter to filter system outputs, a novel fault detection filter is proposed to estimate system states and generate residual signals. Secondly, the properties of the consensus filter are analyzed in detail, and the existence of the proposed fault detection filter is rigorously investigated in terms of linear matrix inequalities. An outstanding feature of the proposed scheme is that the influence of system stochastic noises on residual signals is reduced greatly, and, as a result, fault detection accuracy can be improved dramatically.

An outline of this paper is as follows. In Section 2, we define a class of nonlinear stochastic systems and give some preliminaries. In Section 3, a fault detection observer is proposed to detect system faults. The stability analysis of the consensus filter and the existence of the proposed fault detection filter are rigorously investigated. Finally, in Section 4, some simulation results are reported to illustrate the effectiveness of the proposed fault detection scheme. Some conclusion remarks are provided in Section 5.

2. Problem Statement and Preliminaries

Consider a class of nonlinear stochastic systems described by

$$\dot{x}(t) = Ax(t) + \Phi(x,u) + B_d d(t) + B_f f(t), \quad (1)$$

$$y(t) = Cx(t), \quad (2)$$

where $x(t) \in R^n$ is the system state vector, $u(t) \in R^m$ is the control input vector, $y(t) \in R^q$ is the measurement output vector, $d(t)$ is a zero-mean Gaussian white-noise process, $f(t) \in R^m$ is the system fault to be detected, and $\Phi(x,u)$ is a known nonlinear function. A, B_f, B_d, and C are known parameter matrices with appropriate dimensions. Throughout this paper, we take the following assumptions.

Assumption 1. System faults $f(t)$ and stochastic noises $d(t)$ are bounded, that is, $\|f(t)\| \le N_1$, and $\|d(t)\| \le N_2$.

Assumption 2. The nonlinear function $\Phi(\cdot)$ satisfies Lipschitz condition: that is,

$$\|\Phi(x(t),t) - \Phi(y(t),t)\| \le a\|(x(t) - y(t))\|, \quad \forall x(t), y(t) \in D, \quad (3)$$

where a is a known real constant.

In order to estimate system states, one gives the following full order Luenberger-like observer [13–16]:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + \Phi(\hat{x},u) + H(y - C\hat{x}), \quad (4)$$

where H is a gain matrix to be determined. In order to detect system faults, one constructs the nonlinear fault detection filter as follows:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + \Phi(\hat{x},u) + H(y - C\hat{x}), \quad (5)$$

$$\hat{y}(t) = C\hat{x}(t), \quad (6)$$

$$r(t) = y(t) - \hat{y}(t), \quad (7)$$

where $\hat{x}(t) \in R^n$ and $\hat{y}(t) \in R^q$ represent the estimated states and outputs vectors, respectively. H is a $n \times q$ design gain matrix. $r(t)$ is the so-called generated residual signal. Define states estimation error $e(t) = x(t) - \hat{x}(t)$, and it follows from (1) to (7) that

$$\dot{e}(t) = (A - HC)e(t) + B_f f(t) + B_d d(t) + \Phi - \widehat{\Phi}, \quad (8)$$

$$r(t) = Ce(t), \quad (9)$$

where $\Phi \triangleq \Phi(x,u)$ and $\widehat{\Phi} \triangleq \Phi(\hat{x},u)$. The gain matrix H is to be designed such that systems (5)–(7) are asymptotically stable.

We can clearly see from (5) to (7) that estimation errors of system states and system outputs are all corrupted by stochastic noises, which will lead to false alarms. In order to improve fault detection accuracy, a nonlinear fault detection observer is needed to minimize the influence of the system stochastic noise on residual signals. Therefore, we convert this problem to the following optimization problem: finding a gain matrix H, such that system (8) and (9) remains asymptotically stable, and the performance index $J = \|T_{\mathrm{rd}}\|_\infty$ is minimized. Here, T_{rd} denotes the transfer function from system stochastic noises to residual signals. From (8) and (9), we can see that dynamics of the residual signals depend not only on $f(t)$ and $d(t)$ but also on nonlinear part: $\Phi - \widehat{\Phi}$. So the existing design techniques for fault detection observer cannot

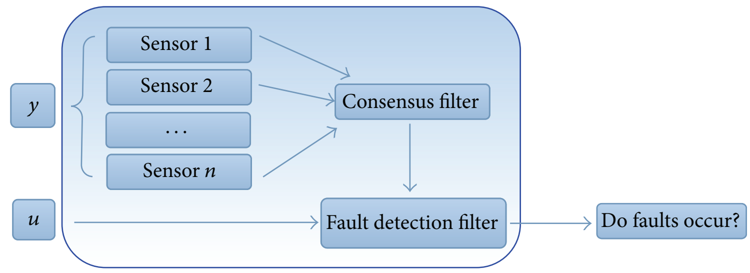

FIGURE 1: Architecture of fault detection observer.

be used here. In this paper, we propose a novel distributed fault detection approach by combining a consensus filter with a nonlinear fault detection filter. The selection of matrix H will be given in terms of LMIs in Section 3.

3. Main Results

In this section, we will give detailed design procedures for fault detection observer. The stability analysis of consensus filter and the existence of the fault detection filter are rigorously investigated.

3.1. Fault Detection Observer Design. Generally speaking, it is often difficult to get an exact description of a real plant system. Some unavoidable stochastic noises will have an influence on the practical engineering systems. As a result, some false alarms will be generated using the existing fault detection techniques. Also, with the increasing complexity of a real plant system, it is inevitable to use distributed sensors to measure system outputs at the same time. Take the high voltage direct current transmission system, for instance, we have to use distributed sensors to measure voltages, currents, and resistors along the transmission lines. Therefore, distributed fault diagnosis schemes are now attracting a lot of attentions from researchers.

In this work, we propose a novel distributed fault detection observer for a class of nonlinear stochastic systems. From (5) to (7), we can clearly see that the estimation errors of system states and outputs are affected by stochastic noises. It is difficult to detect the nonlinear stochastic systems faults using residual signals generated by a fault detection filter. To improve the fault detection accuracy, we develop a novel fault detection observer to detect system faults, which consists of a consensus filter and a fault detection filter. Firstly, a bank of distributed sensors is used to measure the system outputs. Secondly, each sensor sends its data to the consensus filter. The consensus filter acts as a data fusion center to reduce the influence of stochastic noises on residual signals. Then, a novel fault detection filter is developed by combining system control inputs with outputs of the consensus filter. Due to the existence of stochastic noises, one thing we have to consider is that to what extent the stochastic noises will have an influence on the residual signals. The whole architecture of the proposed fault detection scheme is shown in Figure 1.

For the convenience of designing the fault detection observer, we rewrite (5)–(7) as follows:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + \Phi(\hat{x}, u) + L(\overline{y} - C\hat{x}), \tag{10}$$

$$\hat{y}(t) = C\hat{x}(t), \tag{11}$$

$$z_i(t) = \tilde{y}_i(t) - y(t), \quad (i = 0, 1, \ldots, n), \tag{12}$$

$$r(t) = \overline{y}(t) - \hat{y}(t), \tag{13}$$

where $\overline{y}(t)$ is outputs of the consensus filter. $\tilde{y}(t)$ is the state of each node in consensus filter. To minimize the influence of nonlinear system stochastic noises on residual signals, it leads to the following optimization problem: finding gain matrix L, such that system (10)–(13) remains asymptotically stable, and the performance index $J = \|T_{rd}\|_\infty$ is minimized.

3.2. Stability Analysis of Consensus Filter. In recent years, the study of information flow and coordination among different dynamic agents had aroused a larger amount of interests for researchers from all over the world. Among them, how to control each agent in a group to reach consensus is the key point in the condition that information exchange is limited and unreliable. The conceptions and ideas of consensus filter can be found in [17–29] and references therein.

Theorem 3. *Suppose that system* (1) *and* (2) *satisfies the Assumptions 1 and 2, and the fault diagnosis observer holds the form of* (10)–(13). *Then the consensus filter is asymptotically ε stable with each node state $\eta^* = z(t)P$, where*

$$\begin{aligned}\varepsilon = {} & \Big(\|C\| \left[(\|A - LC\| + \alpha)\sigma + N_1 \left\|B_f\right\| + N_2 \left\|B_d\right\|\right] \\ & \times \sqrt{n}\left(1 + d_{\max}\right)\lambda_{\min}^{1/2}(M)\Big) \\ & \times \left(\lambda_{\min}^{5/2}(M)\right)^{-1},\end{aligned} \tag{14}$$

η denotes the node of a small world networks G, $M = \{m_{ij}\}$ is the relation topology matrix of G, $Z(t)$ is the expected output of the consensus filter, and $P = \underbrace{[1, 1, \ldots, 1]}_{n}{}^T$.

Proof. From (10)–(12) and the definition of state estimation errors $e(t) = x(t) - \hat{x}(t)$, the maximum estimation errors of system states can be expressed as follows: $\sigma = \mathrm{MAX}(e(t))$.

We choose small world networks G as the weighed graph of the consensus filter. Let η denote a set of nodes in graph G with size n. $z(t)$ is the input of the consensus filter, that is, the state of each node is $z(t)P$.

Let $\delta = \eta - z(t)P$, then we have

$$\dot{\delta} = -M\delta + \dot{z}(t)P, \tag{15}$$

where M is a positive definite matrix with property

$$(1 + d_{\min}) \le \lambda_{\min}(M) \le \lambda_{\max}(M) \le (1 + 3d_{\max}). \tag{16}$$

For system (12), we select the Lyapunov function as follows:

$$V = \frac{1}{2}\delta^T M\delta. \tag{17}$$

Then we have

$$\begin{aligned}
\dot{V} &= -\|M\delta\|^2 + \dot{z}(t)\left(P^T M\delta\right) \\
&= -\|M\delta\|^2 \\
&\quad + C\left[(A - LC)e(t) + \Phi - \widehat{\Phi} + B_f f(t) + B_d d(t)\right] \\
&\quad \times \left[(1 + d_1, 1 + d_2, \ldots, 1 + d_n)\delta\right] \\
&\le -\lambda_{\min}^2(M)\|\delta\|^2 \\
&\quad + \|C\|\left(\|A - LC\|\sigma + \alpha\sigma + N_1\left\|B_f\right\| + N_2\|B_d\|\right) \\
&\quad \times \left[\sum_i (1 + d_i)^2\right]^{1/2} \|\delta\| \\
&\le -\lambda_{\min}^2(M)\|\delta\|^2 \\
&\quad + \|C\|\left[(\|A - LC\| + \alpha)\sigma + N_1\left\|B_f\right\| + N_2\|B_d\|\right] \\
&\quad \times \sqrt{n}(1 + d_{\max})\|\delta\| \\
&= -\Big\{\lambda_{\min}(M)\|\delta\| \\
&\qquad - \Big(\|C\|\left[(\|A - LC\| + \alpha)\sigma + N_1\left\|B_f\right\| + N_2\|B_d\|\right] \\
&\qquad\qquad \times \sqrt{n}(1 + d_{\max})\Big)\left(2\lambda_{\min}(M)\right)^{-1}\Big\}^2 \\
&\quad + \Big(\Big(\|C\|\left[(\|A - LC\| + \alpha)\sigma + N_1\left\|B_f\right\| + N_2\|B_d\|\right] \\
&\qquad \times \sqrt{n}(1 + d_{\max})\Big)\left(2\lambda_{\min}(M)\right)^{-1}\Big)^2.
\end{aligned} \tag{18}$$

Define a closed ball X which is centered at zero point, and the radius of the closed ball is

$$\begin{aligned}
r = \Big(&\|C\|\left[(\|A - LC\| + \alpha)\sigma + N_1\left\|B_f\right\| + N_2\|B_d\|\right] \\
&\times \sqrt{n}(1 + d_{\max})\Big)\left(2\lambda_{\min}(M)\right)^{-1}.
\end{aligned} \tag{19}$$

Define a set of Lyapunov functions:

$$\Delta = \left\{\delta : V(\delta) \le \frac{1}{2}\lambda_{\max}(M)r^2\right\}. \tag{20}$$

Then we have $X \subset \Delta$,

$$\|\delta\| \le r \Longrightarrow V(\delta) = \frac{1}{2}\delta^T M\delta \le \frac{1}{2}\lambda_{\max}(M)\delta^2. \tag{21}$$

Thus we have $\delta \in \Delta$. Therefore, the solution of $\dot{\delta} = -M\delta + \dot{z}(t)P$ satisfies $\dot{V}(\rho) < 0$.

This completes the proof. □

According to Theorem 3, we can draw the conclusion that the consensus filter for the nonlinear stochastic systems is asymptotically convergent.

3.3. Design of Fault Detection Filter. In this section, design procedures of fault detection filter are given in details. The matrix parameters are designed in terms of linear matrix inequality using robust control theory and nonlinear matrix inequality methods.

Lemma 4 (see [1]). *Let A and B be real matrices with appropriate dimensions. For any scalar $\varepsilon > 0$ and vectors x, $y \in R^n$, one has $2x^T ABy \le \varepsilon^{-1}x^T AA^T x + \varepsilon y^T B^T By$.*

Theorem 5. *Suppose that the systems (1) and (2) satisfy Assumptions 1 and 2, and the fault detection observer holds the form of (10)–(13). Given a constant $\gamma > 0$, the system (10)–(13) satisfies $\|r(t)\|_\infty \le \gamma\|d(t)\|_\infty$, if there exist a positive symmetrical matrix P and a scalar $\varepsilon_1 > 0$, satisfying the following LMI:*

$$\begin{bmatrix} P(A - LC) + (A - LC)^T P + C^T C + \varepsilon_1\alpha^2 I & 0 & P \\ 0 & -\gamma^2 I & \\ P^T & & -\varepsilon_1 I \end{bmatrix} < 0. \tag{22}$$

Proof. Considering the system (10)–(13), we choose a Lyapunov function of the following form: $V(t) = e^T(t)Pe(t)$, where P is a positive symmetrical matrix. In fault-free case, when system uncertainty $d(t) = 0$, we have

$$\begin{aligned}
\dot{V}(t) &= e^T(t)P\dot{e}(t) + \dot{e}^T(t)Pe(t) \\
&= e^T(t)P\left[(A - LC)e(t) + \Phi - \widehat{\Phi}\right] + \dot{e}^T(t)Pe(t) \\
&= e^T(t)P\left[(A - LC)e(t) + \Phi - \widehat{\Phi}\right] \\
&\quad + \left[(A - LC)e(t) + \Phi - \widehat{\Phi}\right]^T Pe \\
&= e^T(t)\left[P(A - LC) + (A - LC)^T P\right]e(t) \\
&\quad + e^T(t)P\left[\Phi - \widehat{\Phi}\right] + \left[\Phi - \widehat{\Phi}\right]^T Pe.
\end{aligned} \tag{23}$$

According to Lemma 4 and Assumption 2, we have

$$\begin{aligned}
&2e^T(t)P\left[\Phi - \widehat{\Phi}\right] \\
&\quad \le \varepsilon_1^{-1}e^T(t)PP^T e(t) + \varepsilon_1\left(\Phi - \widehat{\Phi}\right)^T\left(\Phi - \widehat{\Phi}\right) \\
&\quad \le \varepsilon_1^{-1}e^T(t)PP^T e(t) + \varepsilon_1\alpha^2 e^T(t)e(t).
\end{aligned} \tag{24}$$

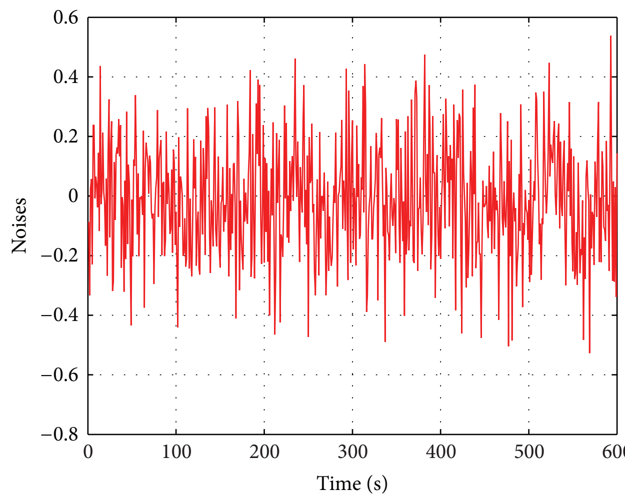

Figure 2: Stochastic noises.

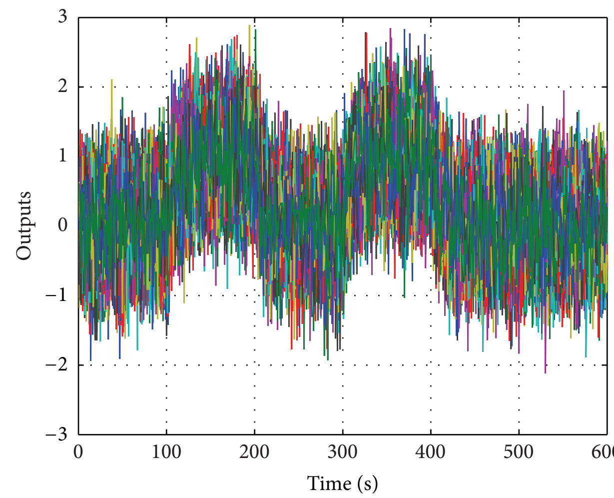

Figure 3: System outputs.

Thus,

$$\dot{V}(t) \leq e^T(t)\left[P(A-LC)+(A-LC)^T P+\varepsilon_1^{-1}PP^T + \varepsilon_1\alpha^2 I\right]e(t). \tag{25}$$

From (22), we can obtain that $\dot{V}(t) \leq 0$.

So the system described by (10)–(13) is asymptotically stable in the condition of no fault.

When the system uncertainty $d(t) \neq 0$, by defining

$$H(e,d) = \dot{V}(t) + \|r(t)\|_\infty - \gamma^2\|d(t)\|_\infty \tag{26}$$

we have

$$\begin{aligned}
H(e,d) &= e^T(t)P\dot{e}(t) + \dot{e}^T(t)Pe(t) + e^T(t)C^TCe(t) \\
&\quad - \gamma^2 d^T(t)d(t) \\
&= e^T(t)P\left[(A-LC)e(t) + B_d d(t) + \Phi - \widehat{\Phi}\right] \\
&\quad + \left[(A-LC)e(t) + \Phi - \widehat{\Phi} + B_d d(t)\right]^T Pe(t) \\
&\quad + e^T(t)C^TCe(t) - \gamma^2 d^T(t)d(t) \\
&\leq e^T(t)\left[P(A-LC)+(A-LC)^TP + \varepsilon_1^{-1}PP^T + C^TC \right. \\
&\quad \left. + \varepsilon_1\alpha^2 I\right]e(t) - \gamma^2 d^T(t)d(t) \\
&= \begin{bmatrix} e(t) \\ d(t) \end{bmatrix}^T \begin{bmatrix} \Lambda & 0 \\ 0 & -\gamma^2 I \end{bmatrix} \begin{bmatrix} e(t) \\ d(t) \end{bmatrix},
\end{aligned} \tag{27}$$

where

$$\Lambda = P(A-LC) + (A-LC)^TP + C^TC + \varepsilon_1^{-1}PP^T + \varepsilon_1\alpha^2 I. \tag{28}$$

From the known condition (22), by using Schur theory we have

$$H(e,d) = \dot{V}(t) + r^T(t)r(t) - \gamma^2 d^T(t)d(t) < 0. \tag{29}$$

For any given time $t > 0$, integration of (29) from 0 to t yields

$$\int_0^{+\infty} r^T(t)r(t) < \gamma^2 \int_0^{+\infty} d^T(t)d(t). \tag{30}$$

Thus, the inequality $\|r(t)\|_\infty \leq \gamma\|d(t)\|_\infty$ holds.

This completes the proof. □

Remark 6. Theorem 5 gives the existence of the fault detection filter. This optimization problem (22) can be solved by using Matlab software toolboxes. In the presence of system stochastic noises, the effects of faults on residual signals are hidden in the stochastic noises. It is difficult to distinguish a real one from the residual signals. Theorem 5 gives us a method to select an approximate gain matrix to design the fault detection filter. One can use residual evaluation function $\|r(t)\|_2$ to detect system faults. As a result, the fault detection accuracy can be improved dramatically.

4. Simulation Results

We consider a class of nonlinear stochastic systems:

$$\begin{aligned}
\dot{x}(t) &= \begin{bmatrix} -0.46 & 0 \\ 0 & -0.53 \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u \\
&\quad + \begin{bmatrix} 0.3\sin(x(t)) & \\ & 0.2\sin(x(t)) \end{bmatrix} \\
&\quad + \begin{bmatrix} 0.3 \\ 0.2 \end{bmatrix} d(t) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} f(t), \\
y(t) &= \begin{bmatrix} 1 & 1 \end{bmatrix} x(t),
\end{aligned} \tag{31}$$

where $d(t)$ is a zero-mean Gaussian white noise. Let $\gamma = 0.3$, $\varepsilon_1 = 0.7$. According to Theorem 5, we determine the gain matrix L with Matlab toolbox: $L = [0.2511, 0.1279]$.

In the simulation study, we take the step-function fault into consideration. Figure 2 shows the zero-mean Gaussian white noises generated by Matlab software. Figure 3 shows

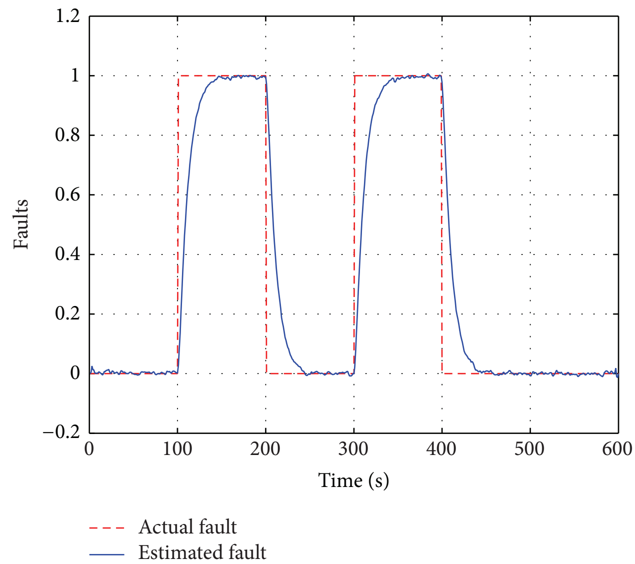

Figure 4: Outputs of fault detection filter.

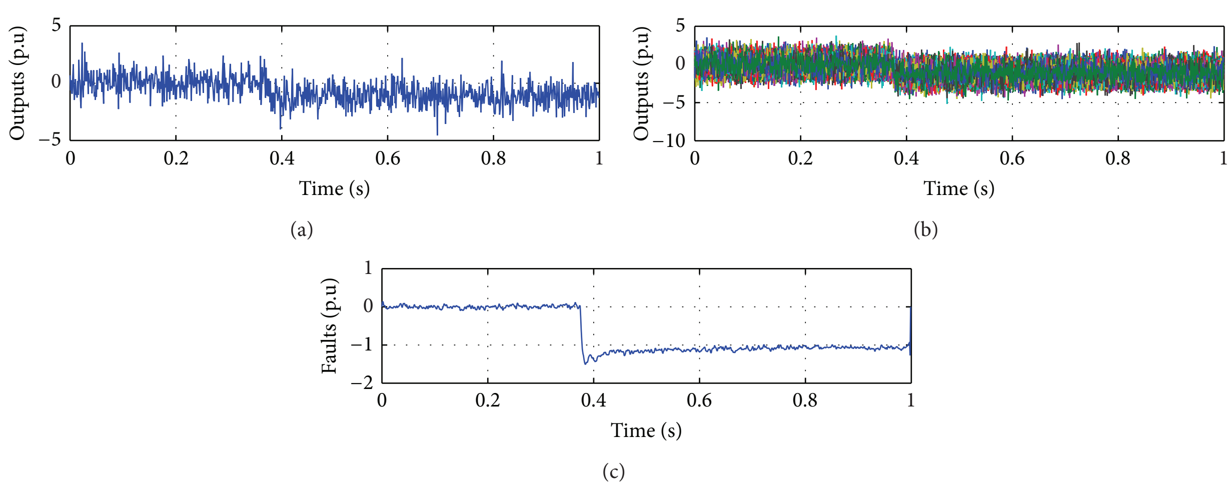

Figure 5: (a) System outputs, (b) measurements by distributed sensors, and (c) outputs of fault detection filter.

the system outputs measured by 100 distributed sensors. Figure 4 shows the outputs of the fault detection filter using the outputs of the consensus filter. From Figure 3, we can see that system outputs are corrupted by stochastic noises, and it is difficult to detect system faults using these system outputs. From Figure 4 we can clearly see that system faults occur at time $t = 100$ s and $t = 300$ s, respectively. As a result, we can detect system faults at time $t = 100$ s and $t = 300$ s, respectively. Figure 5 shows another simulation study by using 100 distributed sensors. In this simulation study, we investigate a step-function fault which occurs at $t = 0.38$ s. From Figure 5(a), we can see that the system faults seem to be hidden by system stochastic noises. Some false alarms may be generated using existing fault detection approaches. We use 100 distributed sensors to measure the system outputs at the same time and then send the measured system outputs to the consensus filter, as is shown in Figure 5(b). A fault detection filter is constructed using outputs of the consensus filter and the system control inputs. Comparing Figure 5(a) with Figure 5(c), we can see that the residual signals generated by fault detection filter can reflect real system faults. Therefore, fault detection accuracy can be improved dramatically.

5. Conclusions

This paper has proposed a novel distributed fault detection scheme for a class of nonlinear stochastic systems. A novel fault detection observer is developed using a consensus filter and a nonlinear fault detection filter. By combining these two kinds of filters, a distributed fault detection observer is designed to minimize the influence of stochastic noises on residual signals. The stability of consensus filter is rigorously analyzed in detail. Meanwhile, the parameter optimization of the fault detection filter is given in terms of LMIs.

In the simulation study, numerical examples are given to demonstrate the validity and applicability of the proposed approach.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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References

[1] P. M. Frank, “Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: a survey and some new results,” *Automatica*, vol. 26, no. 3, pp. 459–474, 1990.

[2] R. Isermann, “Process fault detection based on modeling and estimation methods: a survey,” *Automatica*, vol. 20, no. 4, pp. 387–404, 1984.

[3] Z. Donghua and Y. Yinzhong, *Modern Fault Diagnosis and Fault Tolerant Control*, Publishing Company of Tsinghua University, Beijing, China, 2000.

[4] K. Zhang, B. Jiang, and V. Cocquempot, “Fast adaptive fault estimation and accommodation for nonlinear time-varying delay systems,” *Asian Journal of Control*, vol. 11, no. 6, pp. 643–652, 2009.

[5] M. M. Polycarpou and A. B. Trunov, “Learning approach to nonlinear fault diagnosis: detectability analysis,” *IEEE Transactions on Automatic Control*, vol. 45, no. 4, pp. 806–812, 2000.

[6] X. D. Zhang, M. M. Polycarpou, and T. Parisini, “A robust detection and isolation scheme for abrupt and incipient faults in nonlinear systems,” *IEEE Transactions on Automatic Control*, vol. 47, no. 4, pp. 576–593, 2002.

[7] X. D. Zhang, T. Parisini, and M. M. Polycarpou, “Sensor bias fault isolation in a class of nonlinear systems,” *IEEE Transactions on Automatic Control*, vol. 50, no. 3, pp. 370–376, 2005.

[8] A. T. Vemuri, “Sensor bias fault diagnosis in a class of nonlinear systems,” *IEEE Transactions on Automatic Control*, vol. 46, no. 6, pp. 949–954, 2001.

[9] W. Chen and M. Saif, “An iterative learning observer for fault detection and accommodation in nonlinear time-delay systems,” *International Journal of Robust and Nonlinear Control*, vol. 16, no. 1, pp. 1–19, 2006.

[10] X. Zhang, M. M. Polycarpou, and T. Parisini, “Fault diagnosis of a class of nonlinear uncertain systems with Lipschitz nonlinearities using adaptive estimation,” *Automatica*, vol. 46, no. 2, pp. 290–299, 2010.

[11] L. Guo and H. Wang, “Fault detection and diagnosis for general stochastic systems using B-spline expansions and nonlinear filters,” *IEEE Transactions on Automatic Control*, vol. 52, no. 8, pp. 1644–1652, 2005.

[12] Y. Bingyong, T. Zuohua, and L. Dongmei, “Fault diagnosis for a class of nonlinear stochastic time-delay systems,” *Control and Instruments in Chemical Industry*, vol. 34, no. 1, pp. 12–15, 2007.

[13] W. Zhang, H. Su, H. Wang, and Z. Han, “Full-order and reduced-order observers for one-sided lipschitz nonlinear systems using Riccati equations,” *Communications in Nonlinear Science and Numerical Simulation*, vol. 17, no. 12, pp. 4968–4977, 2012.

[14] W. Zhang, H.-S. Su, Y. Liang, and Z.-Z. Han, “Non-linear observer design for one-sided Lipschitz systems: an linear matrix inequality approach,” *IET Control Theory and Applications*, vol. 6, no. 9, pp. 1297–1303, 2012.

[15] W. Zhang, H. Su, and J. Wang, “Computation of upper bounds for the solution of continuous algebraic Riccati equations,” *Circuits, Systems, and Signal Processing*, vol. 32, no. 3, pp. 1477–1488, 2013.

[16] W. Zhang, X.-S. Cai, and Z.-Z. Han, “Robust stability criteria for systems with interval time-varying delay and nonlinear perturbations,” *Journal of Computational and Applied Mathematics*, vol. 234, no. 1, pp. 174–180, 2010.

[17] H. Su, X. Wang, and Z. Lin, “Flocking of multi-agents with a virtual leader,” *IEEE Transactions on Automatic Control*, vol. 54, no. 2, pp. 293–307, 2009.

[18] H. Su, X. Wang, G. Chen, and Z. Lin, “Adaptive second-order consensus of networked mobile agents with nonlinear dynamics,” *Automatica*, vol. 47, no. 2, pp. 368–375, 2011.

[19] H. Su, Z. Rong, M. Z. Q. Chen, X. Wang, G. Chen, and H. Wang, “Decentralized adaptive pinning control for cluster synchronization of complex dynamical networks,” *IEEE Transactions on Cybernetics*, vol. 43, no. 1, pp. 394–399, 2013.

[20] H. Su, M. Z. Q. Chen, J. Lam, and Z. Lin, “Semi-global leader-following consensus of linear multi-agent systems with input saturation via low gain feedback,” *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 60, no. 7, pp. 1881–1889, 2013.

[21] H. Su, M. Z. Q. Chen, X. Wang, and J. Lam, “Semiglobal observer-based leader-following consensus with input saturation,” *IEEE Transactions on Industrial Electronics*, vol. 61, no. 6, pp. 2842–2850, 2014.

[22] J. A. Fax and R. M. Murray, “Information flow and cooperative control of vehicle formations,” *IEEE Transactions on Automatic Control*, vol. 49, no. 9, pp. 1465–1476, 2004.

[23] A. Jadbabaie, J. Lin, and A. S. Morse, “Coordination of groups of mobile autonomous agents using nearest neighbor rules,” *IEEE Transactions on Automatic Control*, vol. 48, no. 6, pp. 988–1001, 2003.

[24] R. Olfati-Saber and R. M. Murray, “Consensus problems in networks of agents with switching topology and time-delays,” *IEEE Transactions on Automatic Control*, vol. 49, no. 9, pp. 1520–1533, 2004.

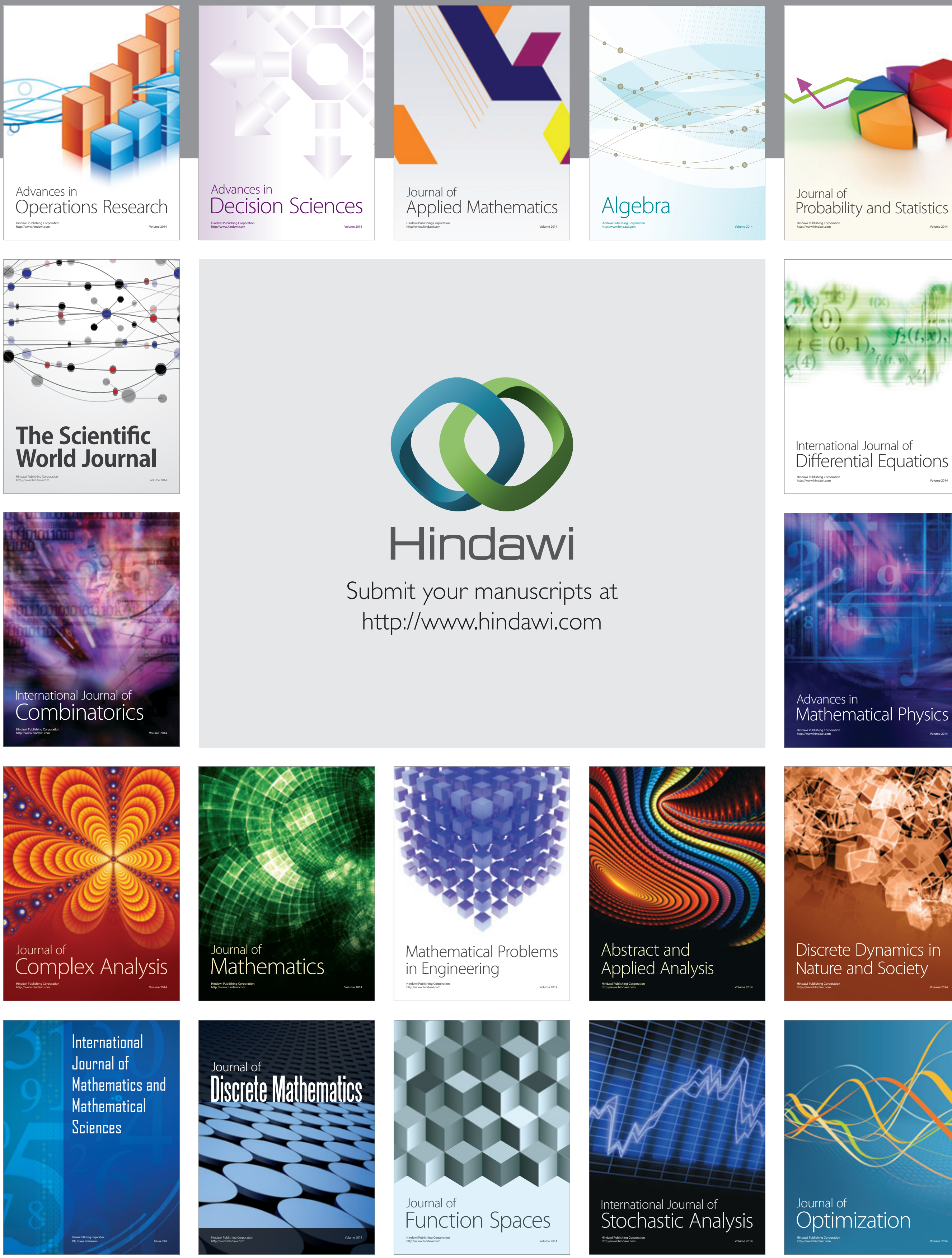
[25] W. Ren, R. W. Beard, and D. B. Kingston, “Multi-agent kalman consensus with relative uncertainty,” in *Proceedings of the American Control Conference (ACC ’05)*, pp. 1865–1870, Portland, Ore, USA, June 2005.

[26] R. Olfati-Saber and J. S. Shamma, “Consensus filters for sensor networks and distributed sensor fusion,” in *Proceeding of the 44th IEEE Conference on Decision and Control, and the European Control Conference (CDC-ECC '05)*, pp. 6698–6703, December 2005.

[27] D. Bauso, L. Giarré, and R. Pesenti, “Distributed consensus protocols for coordinating buyers,” in *Proceedings of the IEEE Conference on Decision and Control*, pp. 588–592, December 2003.

[28] R. Olfati-Saber, "Distributed Kalman filter with embedded consensus filters," in *Proceedings of the 44th IEEE Conference on Decision and Control, and the European Control Conference (CDC-ECC '05)*, pp. 8179–8184, December 2005.

[29] R. Olfati-Saber, "Distributed Kalman filtering and sensor fusion in sensor networks," in *Proceedings of the Workshop on Network Embedded Sensing and Control*, Notre Dame University, South Bend, Ind, USA, October 2005.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