Neurocomputing 191 (2016) 409–420

Contents lists available at ScienceDirect

Neurocomputing

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

Fault detection for nonlinear networked systems based on quantization and dropout compensation: An interval type-2 fuzzy-model method

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ARTICLE INFO

Article history:
Received 14 November 2015
Received in revised form
22 December 2015
Accepted 3 January 2016
Communicated by H. Zhang
Available online 10 February 2016

Keywords:
Nonlinear networked systems
Parameter uncertainties
Fuzzy systems
Fault detection filter

ABSTRACT

This paper investigates the problem of filter-based fault detection for a class of nonlinear networked systems subject to parameter uncertainties in the framework of the interval type-2 (IT2) T–S fuzzy model-based approach. The Bernoulli random distribution process and logarithm quantizer are used to describe the measurement loss and signals quantization, respectively. In the framework of the IT2 T–S fuzzy model, the parameter uncertainty is handled by the membership functions with lower and upper bounds. A novel IT2 fault detection filter is designed to guarantee the residual system to be stochastically stable and satisfy the predefined H_∞ performance. It should be mentioned that the proposed filter does not use the same premise variables, number of fuzzy rules and membership functions as the fuzzy model, which will lead to more flexible design. Finally, two illustrative examples are provided to demonstrate the usefulness of the approach proposed in this paper.

1. Introduction

In practical industrial systems, the plant, sensors, actuators and other components are usually distributed in different geographical locations. Thus, the signal needs to be sent from one place to another. With the rapid development of communication technology, the system components often exchange information via a communication network, which gives rise to networked systems [1,2]. Through applying the communication network, some advantages such as resource sharing, ease of installation and maintenance and remote control are offered. Therefore, networked systems can be employed to improve some applications, including H-bridge converters with nonequal DC link voltages [3] and grid-connected photovoltaic generation plants [4]. However, the network can be affected by some network-induced problems, such as, data packets dropout, network-induced delays and data quantization arising in the networked system, which degrade the performance of system. In view of these network-based characteristics, some results about analyzing and modeling [5,6], the stability and stabilization [7] and the H_∞ filter design results [8] have been reported for networked systems.

Fault detection has been an active research field since the high safety, reliability and performance are demanded in industrial applications [9]. Considerable attention has been paid to the fault detection problem [10–12]. On the other hand, nonlinear systems [13] can be handled via many intelligent strategies, such as fuzzy set theory [14] and neural network [15]. Liu et al. [16] combined fuzzy control and adaptive backstepping control methods, and then proposed an adaptive fuzzy control scheme for systems with backlash. The problem of adaptive fuzzy optimal control for nonlinear systems has been studied in [17]. As an extension, the adaptive fuzzy backstepping control scheme was applied to control multi-input multi-output systems in [18,19]. Li et al. combined adaptive control and sliding mode control in [20]. And neural network was integrated into the framework of adaptive backstepping control in [21,22]. Takagi–Sugeno (T–S) fuzzy model was proposed to model nonlinear systems, and it can approximate the nonlinearity to any certain degree of accuracy by using the "IF-THEN" rules, which has been applied successfully in [23] and [24]. The authors in [25] investigated the problem of reliable control for nonlinear hyperbolic PDE systems on the basis of such model, obtaining nice results. A variety of fault detection problems

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http://dx.doi.org/10.1016/j.neucom.2016.01.061
0925-2312/

for nonlinear networked systems have been investigated, including systems with measurement loss [26,27], systems with network-induced delays [28], and systems with quantization [29].

However, it is worth noting that the aforementioned results are based on the type-1 T–S fuzzy model, through which the nonlinearity can be approximated quite effectively. The industrial environment is quite complex such that it may result in parameter uncertainties. However, membership functions of the type-1 fuzzy system are fixed, which can lead to an incomplete description for the uncertainties and may degrade the system performance. Compared with type-1 fuzzy set, type-2 one can describe uncertainties more effectively [30]. However, the terrible computational complexity of such theory makes it difficult to understand and apply to engineering applications. The more accessible computing strategy was proposed for type-2 fuzzy set in [31]. The authors in [32] proposed an interval type-2 (IT2) fuzzy model approach to capture the uncertainties, in which the membership functions are given in the form of interval, and thus, the parameter uncertainties can be captured. Recently, some results have been published in open literatures, see for instance [33,34] and references therein. In [35], the concept of lower and upper membership functions was introduced to describe the uncertain membership functions and the superiority of IT2 fuzzy model over type-1 approach has been proven. To extend the application of IT2 model, within utilizing the lower and upper membership functions, the IT2 T–S fuzzy model was proposed in [36] and stabilization conditions were derived. The authors in [37] and [38] designed an IT2 controller with imperfect premise matching, which enhanced the design flexibility. With mismatched membership functions, both state-feedback control and static output-feedback control schemes were investigated via the IT2 T–S fuzzy model in [39]. In [40], the filter for IT2 fuzzy systems with D-stable constraints was designed under a unified frame. An IT2 switched output-feedback based control scheme was applied to mass-spring-damping system in [41]. Considering favorite properties of IT2 T–S fuzzy model, a state-feedback control scheme was proposed for nonlinear networked systems with parameters uncertainties in [42]. In the case of immeasurable state, an observer-based control scheme was proposed in [43], and the authors in [44] designed an IT2 filter for a class of nonlinear networked systems. To address the systems with sensor fault, Li et al. [45] provided an observer-based fault detection strategy for systems subject to limited communication capacity. However, to the authors' best knowledge, there exist few fault detection results concerning networked systems in literature.

Motivated by the above discussions, this paper focuses on the problem of fault detection filter (FDF) design for a class of nonlinear networked systems with parameter uncertainties. Imperfect communication links and signals quantization are considered. The main contributions can be summarized as follows: (1) The system with parameter uncertainties is modeled in terms of an IT2 T–S fuzzy model, which can capture the uncertainties with lower and upper membership functions and improve the capability of describing complex systems. (2) The premise variables, number of fuzzy rules and membership functions of the FDF to be designed are independent of those of the system model, which, to some degree, increases the flexibility of designing the FDF, decreases the total number of system rules and deserves less conservative results. (3) The footprint of uncertainty (FOU) is considered, and thus, more uncertain information can be captured. Moreover, the achieved stable criteria become membership function-dependent, which facilitate obtaining less conservative conditions. Finally, two illustrative examples are provided to illustrate the effectiveness of the method proposed in this paper.

The remainder of the paper is organized as follows. Section 2 describes the problem of fault detection subject to data packets dropout, signals quantization and parameter uncertainties. The residual system analysis and the conditions of designing the FDF are formulated in Section 3. Two illustrative examples are provided to verify the usefulness of the proposed method in Section 4. Finally, Section 5 concludes the paper.

Notation: The notation utilized in this paper is quite standard. The superscript "T" and "-1" denote matrix transposition and matrix inverse, respectively. The identity matrix and zero matrix with compatible dimensions are represented by I and 0, respectively. The notation $P>0(\geq 0)$ suggests that P is positive definite (semi-definite) with the real symmetric structure. $l_2[0,\infty)$ means the space of square-integrable vector functions over $[0,\infty)$; R^n describes the n-dimensional Euclidean space and $\|\cdot\|_2$ shows the usual $l_2[0,\infty)$ norm. In complex matrices, the symbol $(*)$ and diag{ …} are used to describe the symmetric term and matrix with block diagonal structure, respectively. Furthermore, $E\{x|y\}$ and $E\{x\}$ signify expectation of x conditional on y and expectation of x, respectively. Matrices in this paper without dimensions explicitly stated, we assume they have compatible dimensions.

2. Problem formulation

Consider a nonlinear networked system subject to parameter uncertainties based on the IT2 T–S fuzzy model as follows:

Plant Rule i: IF $f_1(\sigma(k))$ is M_{i1}, and $f_2(\sigma(k))$ is M_{i2} and, …, and $f_\theta(\sigma(k))$ is $M_{i\theta}$, THEN

$$\begin{aligned}&x(k+1)=A_ix(k)+B_iu(k)+E_{1i}w(k)+E_{2i}f(k),\\&y(k)=C_ix(k)+D_iu(k)+F_{1i}w(k)+F_{2i}f(k),\quad i=1,2,\ldots,r,\end{aligned}\tag{1}$$

where M_{ij} denotes the fuzzy set, and $f(\sigma(k))=[f_1(\sigma(k)),f_2(\sigma(k)),\ldots,f_\theta(\sigma(k))]^T$ stands for the premise variable, in which $\sigma(k)$ may depend on the system state. $x(k)\in R^{n_x}$ represents the state; $y(k)\in R^{n_y}$ stands for the measured output; $u(k)\in R^{n_u}$ denotes the control input; $w(k)\in R^{n_w}$ and $f(k)\in R^{n_f}$ stand for the external disturbance and the fault vector to be detected, respectively, which belong to $l_2[0,\infty)$. A_i, B_i, E_{1i}, E_{2i}, C_i, D_i, F_{1i} and F_{2i} are system matrices with appropriate dimensions. The scalar r is the number of "IF-THEN" rules of the system. The following interval sets present the firing strength of the ith rule:

$$W_i(\sigma(k))=[\underline{m}_i(\sigma(k)),\overline{m}_i(\sigma(k))],$$

where

$$\underline{m}_i(\sigma(k))=\prod_{p=1}^{\theta}\underline{u}_{M_{ip}}(f_p(\sigma(k)))\geq 0,\quad \overline{m}_i(\sigma(k))=\prod_{p=1}^{\theta}\overline{u}_{M_{ip}}(f_p(\sigma(k)))\geq 0,\tag{2}$$

$$\overline{u}_{M_{ip}}(f_p(\sigma(k)))\geq\underline{u}_{M_{ip}}(f_p(\sigma(k)))\geq 0,\quad \overline{m}_i(\sigma(k))\geq\underline{m}_i(\sigma(k))\geq 0,\tag{3}$$

$\underline{u}_{M_{ip}}(f_p(\sigma(k)))$, $\overline{u}_{M_{ip}}(f_p(\sigma(k)))$, $\underline{m}_i(\sigma(k))$ and $\overline{m}_i(\sigma(k))$ denote the lower and upper membership functions, the lower and upper grade of membership, respectively.

The overall dynamics of the IT2 T–S model (1) can be represented as follows:

$$\begin{aligned}x(k+1)&=\sum_{i=1}^{r}m_i(\sigma(k))\left[A_ix(k)+B_iu(k)+E_{1i}w(k)+E_{2i}f(k)\right],\\y(k)&=\sum_{i=1}^{r}m_i(\sigma(k))[C_ix(k)+D_iu(k)+F_{1i}w(k)+F_{2i}f(k)],\end{aligned}\tag{4}$$

where

$$m_i(\sigma(k))=\frac{\underline{a}_i(\sigma(k))\underline{m}_i(\sigma(k))+\overline{a}_i(\sigma(k))\overline{m}_i(\sigma(k))}{\sum_{i_1=1}^{r}(\underline{a}_{i_1}(\sigma(k))\underline{m}_{i_1}(\sigma(k))+\overline{a}_{i_1}(\sigma(k))\overline{m}_i(\sigma(k)))}\geq 0,\tag{5}$$

$$\begin{aligned}&0\leq\underline{a}_i(\sigma(k))\leq 1,\quad 0\leq\overline{a}_{i_1}(\sigma(k))\leq 1,\\&\sum_{i=1}^{r}m_i(\sigma(k))=1,\quad \underline{a}_i(\sigma(k))+\overline{a}_i(\sigma(k))=1\end{aligned}\tag{6}$$