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Interval observer-based fault detection in finite frequency domain for discrete-time fuzzy systems

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ABSTRACT

This paper presents a new method for detecting faults in discrete-time fuzzy systems. First, the piecewise interval observers are constructed based on the output-space partition technique. Second, l_1 performance is introduced to attenuate the persistent bounded disturbances and H_- performance in finite frequency domain is employed to improve fault sensitivity of the residual intervals. Then, the observer gains can be determined by solving the disturbance attenuation, fault sensitivity and non-negativity conditions, simultaneously. Different from the classical fault detection methods with residual evaluation functions and threshold generators, the proposed interval observers are able to generate the natural thresholds. Finally, the developed technique is demonstrated in a simulation example.

1. Introduction

Fuzzy systems have aroused more attention due to the advantage in representing the nonlinear systems [1–9]. Common Lyapunov functions [10,11] and piecewise Lyapunov functions [12–14] have been adopted to design controllers and filters. It has been shown that the piecewise Lyapunov function can handle a larger class of fuzzy systems. Fault detection (FD) has become increasingly significant since greater safety demands. Some relatively mature FD methods have been proposed for fuzzy systems (e.g. [15–17]).

Interval observer provides an ideal tool for estimating the states. In [18] and [19], the interval observers were constructed by two Luenberger observers. In [20], interval property was guaranteed by introducing a transformation of coordinates. Furthermore, L_1/L_2 performance was considered in [21] to optimize the estimation accuracy. But the non-negativity was formulated as LMIs with a particular restriction. In [22], the property of Metzler matrix can be characterized as LMIs. In [23], two added non-negative matrices were introduced such that Metzler property is easier to realize. Furthermore, a five-step algorithm for solving the interval observers was given in [24], by fixing some matrices in advance, the LMIs were solved on a grid or iteratively. The concept of intervals has been used in FD (e.g. [25] and [26]). Last but not least, the interval observer-based fault diagnosis has been presented in [27] and [28].

In practical systems, the disturbance signals are mainly persistent bounded and exist in every frequency range. However, the fault signals may exist in finite frequency (FF) range. To describe the different frequency ranges, the frequency characteristic inequalities were introduced in [29]. With the aid of the technique and Lyapunov function method, FF H_∞ filter problem was solved in [30]. In view of the difference in the frequency range between disturbance and fault signals, the FF technique has been used for detecting the faults [31].

This paper proposes a novel FF interval observer-based strategy for detecting the faults in discrete-time fuzzy systems. First, the piecewise interval observers are constructed based on output-space partition. Second, the robustness of the residual intervals against persistent bounded disturbances is improved by introducing l_1 performance. At the same time, the sensitivity to the fault is enhanced by characterizing the H_- specification in low frequency (LF) range. The same slack matrices are introduced by dilated LMI and Projection lemmas, multiple piecewise Lyapunov functions can be employed due to decoupling between the system and Lyapunov matrices. Then the observer design objectives can be achieved by solving a series of LMI conditions simultaneously. Finally, an alarm signal is released and the fault is indicated when the zero value is excluded from the residual interval.

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On the one hand, the classical FD method (see [32,33] and references therein) focuses on computing the residual evaluation functions and thresholds, the FD scheme is designed by making comparisons between the former and the latter. It is worth mentioning that threshold setting is very critical and especially difficult to detect the faults. Although many scholars have devoted themselves to design thresholds, for example, the constant thresholds (e.g., [34] and [35]) and the time-varying thresholds (e.g., [36–39]), the threshold setting remains challenging. On the other hand, the existing interval observer-based FD method [27,28] are developed in full frequency domain, the frequency of the signals has not been fully considered. Different from the above-mentioned FD results, the contributions of this paper are as follows:

1. The interval observers are built to generate the natural time-varying thresholds. The FD scheme does not need the residual evaluation functions and the threshold generators.
2. The finite frequency H_- performance is investigated such that the frequency of the fault signal is fully taken into account and the fault sensitivity is improved directly.

The rest of the paper begins with the fuzzy model, FD interval observers and design objectives in Section 2. Section 3 gives the analysis and design of the interval observer and FD scheme. An example is shown in Section 4 followed by conclusions in Section 5.

Notation: For vectors $\varepsilon=[\varepsilon_i]_{n\times 1}$, $\varsigma=[\varsigma_i]_{n\times 1}$, $\varepsilon\preceq\varsigma$ ($\varepsilon\succeq\varsigma$) denotes $\varepsilon_i\le\varsigma_i$ ($\varepsilon_i\ge\varsigma_i$), $\forall 1\le i\le n$. M^* represents the complex conjugate transpose of a matrix M. $\tilde{E}$ denotes the discrete-time Fourier transform of a signal e. The symmetric terms in a matrix are denoted by $\star$. For given matrix $N\in\mathbb{R}^{m\times n}$, define $N^+=\max\{0,N\}$ and $N^-=N^+-N$.

2. System description and problem statement

2.1. Fuzzy models

Consider the following fuzzy dynamic model:

$$\begin{aligned} x(k+1)&=\sum_{g=1}^{\mu}h_g(y(k))[A_gx(k)+B_gd(k)+E_gf(k)]\\ y(k)&=\sum_{g=1}^{\mu}h_g(y(k))C_gx(k) \end{aligned}\tag{1}$$

where $x(k)\in\mathbb{R}^n$, $y(k)\in\mathbb{R}^q$ are the state and output vectors. $d(k)\in\mathbb{R}^p$ denotes the external disturbance and $f(k)\in\mathbb{R}^s$ denotes the fault signal that belongs to $l_2[0,\infty)$. $A_g\in\mathbb{R}^{n\times n}$, $B_g\in\mathbb{R}^{n\times p}$, $E_g\in\mathbb{R}^{n\times s}$, $C_g\in\mathbb{R}^{q\times n}$ are known constant matrices and $(A_g,\ C_g)$ is observable.

Firstly, inspired by Johansson et al. [12], the output-space is partitioned into operating regions and interpolation regions. $\{S_l\}_{l\in F}\subseteq\mathbb{R}^q$ is a partition of the output $y(k)$ and F is the set of cell indexes. For each cell S_l, the set $K(l)$ contains the indexes for the system matrices used in the interpolation within that cell. For operating regions, $K(l)$ contains a single element. Hence, in each cell, the fuzzy subsystem in (1) can be written as a convex combination of $m\in K(l)$ models:

$$\begin{aligned} x(k+1)&=\sum_{m\in K(l)}h_m(y(k))[A_mx(k)+B_md(k)+E_mf(k)]\\ y(k)&=\sum_{m\in K(l)}h_m(y(k))C_mx(k),\quad y(k)\in S_l,\quad l\in F \end{aligned}\tag{2}$$

where $h_m(y(k))>0$, $\sum_{m\in K(l)}h_m(y(k))=1$.

Assumption 1. There exist the known bound functions $\underline{d}(k)\in\mathbb{R}^p$ and $\overline{d}(k)\in\mathbb{R}^p$ such that

$$\underline{d}(k)\preceq d(k)\preceq\overline{d}(k).\tag{3}$$

Remark 1. Assumption 1 means that the upper and lower bounds on the disturbances are known, it is a standard assumption for interval observer design [18–21].

2.2. Problem statement

In this subsection, the following piecewise interval observer is designed for the system (2):

$$\begin{aligned} \underline{x}(k+1)&=\sum_{m\in K(l)}h_m(y(k))[(A_m-\underline{L}_lC_m)\underline{x}(k)\\ &\quad+B_m^+\underline{d}(k)-B_m^-\overline{d}(k)]\\ &\quad+\underline{L}_ly(k)-\underline{H}_l(\overline{x}(k)-\underline{x}(k))\\ \overline{x}(k+1)&=\sum_{m\in K(l)}h_m(y(k))[(A_m-\overline{L}_lC_m)\overline{x}(k)\\ &\quad+B_m^+\overline{d}(k)-B_m^-\underline{d}(k)]\\ &\quad+\overline{L}_ly(k)+\overline{H}_l(\overline{x}(k)-\underline{x}(k))\\ \underline{y}(k)&=\sum_{m\in K(l)}h_m(y(k))[C_m^+\underline{x}(k)-C_m^-\overline{x}(k)]\\ \overline{y}(k)&=\sum_{m\in K(l)}h_m(y(k))[C_m^+\overline{x}(k)-C_m^-\underline{x}(k)]\\ &\quad y(k)\in S_l,\ l\in F \end{aligned}\tag{4}$$

where $\underline{x}(k)\in\mathbb{R}^n$ and $\overline{x}(k)\in\mathbb{R}^n$ are the lower and upper estimates of $x(k)$. $\underline{y}(k)\in\mathbb{R}^q$ and $\overline{y}(k)\in\mathbb{R}^q$ are the lower and upper estimates of $y(k)$. $\underline{L}_l\in\mathbb{R}^{n\times q}$, $\overline{L}_l\in\mathbb{R}^{n\times q}$, $\underline{H}_l\in\mathbb{R}^{n\times n}$ and $\overline{H}_l\in\mathbb{R}^{n\times n}$ are the undetermined gains.

Define the state estimate errors are $\underline{e}(k)=x(k)-\underline{x}(k)$ and $\overline{e}(k)=\overline{x}(k)-x(k)$, the residual signals are $\underline{r}(k)=y(k)-\overline{y}(k)$ and $\overline{r}(k)=y(k)-\underline{y}(k)$. Then the error dynamics is governed by

$$\begin{aligned} \underline{e}(k+1)&=\sum_{m\in K(l)}h_m(y(k))\{(A_m-\underline{L}_lC_m+\underline{H}_l)\underline{e}(k)+\underline{H}_l\overline{e}(k)\\ &\quad+B_md(k)-[B_m^+\underline{d}(k)-B_m^-\overline{d}(k)]+E_mf(k)\}\\ \overline{e}(k+1)&=\sum_{m\in K(l)}h_m(y(k))\{(A_m-\overline{L}_lC_m+\overline{H}_l)\overline{e}(k)+\overline{H}_l\underline{e}(k)\\ &\quad+B_m^+\overline{d}(k)-B_m^-\underline{d}(k)-B_md(k)-E_mf(k)\}\\ \underline{r}(k)&=\sum_{m\in K(l)}h_m(y(k))[-C_m^+\overline{e}(k)-C_m^-\underline{e}(k)]\\ \overline{r}(k)&=\sum_{m\in K(l)}h_m(y(k))[C_m^+\underline{e}(k)+C_m^-\overline{e}(k)]\\ &\quad y(k)\in S_l,\ l\in F \end{aligned}\tag{5}$$

By considering Assumption 1, the following relations hold:

$$\begin{aligned} &B_md(k)-[B_m^+\underline{d}(k)-B_m^-\overline{d}(k)]\succeq 0,\\ &B_m^+\overline{d}(k)-B_m^-\underline{d}(k)-B_md(k)\succeq 0. \end{aligned}$$

If the matrices $A_m-\underline{L}_lC_m+\underline{H}_l$, $A_m-\overline{L}_lC_m+\overline{H}_l$, $\underline{H}_l$ and $\overline{H}_l$ are nonnegative, then for any initial state $x(0)$ belongs to a certain interval $[\underline{x}(0),\overline{x}(0)]$, $0\in[\underline{r}_z(k),\overline{r}_z(k)]$, $z=1,2,\ldots,q$ hold in the fault-free case.

Remark 2. The residual intervals formed by $\underline{r}_z(k)$ and $\overline{r}_z(k)$ are the key to detection. As discussed in [27,28], the interval characteristic derives from the non-negativity of the error dynamics (5).

The augmented error dynamics is made up due to coupling between the lower and upper errors.

$$\tilde{e}(k+1)=\sum_{m\in K(l)}h_m(y(k))[\tilde{A}_m\tilde{e}(k)+\tilde{B}_m\tilde{d}(k)+\tilde{E}_mf(k)]$$

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