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Event-based fault detection for T–S fuzzy systems with packet dropouts and (*x*, *v*)-dependent noises[☆]

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ABSTRACT

This paper deals with the event-based fault detection problem for T–S fuzzy systems with packet dropouts as well as state- and disturbance-dependent noises ((*x*, *v*)-dependent noises for short). To utilize limited network resources efficiently, the event-triggered mechanism is employed such that only selected valuable data is transmitted to the filter according to whether specific events happen or not. The aim of the addressed problem is to design a fuzzy fault detection filter which guarantees the stochastic stability of the overall fault detection dynamics as well as the robustness against disturbances and sensitivity to faults of the residual signal. Some sufficient criteria are obtained for the existence of the desired fault detection filter which can be designed by solving a set of linear matrix inequalities. Finally, a numerical example is presented to illustrate the validity of the derived results.

1. Introduction

Over the past decades, the fault detection problem has been widely investigated due to the increasing demand for guaranteeing higher performances, higher safety and reliability standards in chemical, automotive and aerospace industries, see e.g. [1–9]. In order to improve the sensitivity to faults and the robustness against disturbances of the fault detection filter, many performance indices such as H_-, H_∞ and mixed H_-/H_∞ have been proposed, see e.g. [10–13]. For example, by using the H_- index and its LMI-based characterization, a complete LMI formulation has been developed in [10] for the problems of H_- index and multi-objective H_-/H_∞ fault detection for linear time-invariant systems. By applying Krein space projection and innovation analysis, the problem of finite horizon H_∞ fault detection has been studied in [11] for linear discrete time-varying systems. Based on the two-player zero-sum game theory, the H_-/H_∞ fault detection filter has been designed in [13] for discrete-time nonlinear systems by means of coupled Hamilton–Jacobi inequalities.

The nonlinearity has been recognized to exist generally in practical devices, and the Takagi–Sugeno (T–S) fuzzy technique has been regarded as a powerful tool to deal with the filter and control problems of nonlinear systems, see e.g. [14–18]. In the past few years, there have appeared some new results on the fault detection and isolation for the nonlinear systems in the T-S fuzzy form, see [12,19–23]. For example, by considering the sensor fault as an auxiliary state variable, a robust fault detection filter has been designed in [12] for a T–S fuzzy model with sensor faults and unknown bounded disturbances. Recently, there has been an increasing interest in the study of T–S fuzzy systems with multiplicative noises, while most references have assumed that the system is subject to state-dependent noises [19,24,25]. However, such an assumption may not reflect the reality closely because the external disturbances could also be corrupted by stochastic noises [26,27]. To the best of our knowledge, the fault detection problem for T–S fuzzy systems with state- and disturbance-noises ((*x*, *v*)-dependent noises for short) has not been investigated yet.

On the other hand, networked control systems (NCSs) have attracted considerable research attention [28–31]. So far, most reported results have been concerned with the control and filtering problems of NCSs, while the problem of fault detection has gained relatively less attention in the context of NCSs [32–36]. For instance, the fault detection filter design problem has been discussed in [35] for a class of networked multi-rate systems with randomly occurring faults and fading channels by using the stochastic analysis approach. Recently, due to the limited communication resources in networked systems, the event-triggered mechanism has

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attracted an ever-increasing research interest for the energy-saving purposes [37–43]. Based on a predefined triggering condition, the event-triggered strategy is employed to determine whether or not the information received by sensors should be transmitted to controllers/filters. In such a case, the efficiency of the resource utilization would be improved by reducing the unnecessary executions in NCSs. Unfortunately, up to now, the event-based fault detection problem for T–S fuzzy systems with packet dropouts has not been investigated, not to mention the case when the system is subject to (x, v)-dependent noises as well.

Motivated by the above discussions, in this paper, we aim to deal with the event-based fault detection problem for T–S fuzzy systems with packet dropouts and (x, v)-dependent noises. Two pre-specified constraints are introduced in the design of the fault detection filter to reflect its robustness against disturbances and sensitivity to faults, respectively. Some sufficient conditions are derived for the existence of the fuzzy fault detection filter, and these conditions can be solved by using linear matrix inequality technique. *The main contributions of this paper can be briefly outlined as follows. (1) The event-based mechanism is proposed for the fault detection problem of T–S fuzzy systems in order to reduce the frequency of data transfer and save valuable network resources. (2) The T–S fuzzy model under study is comprehensive that includes packet dropouts and (x, v)-dependent noises. (3) Stochastic analysis is carried out to enforce multiple requirements, including the mean-square convergence of detection errors, the restraint on disturbances and the sensitivity to faults of residual signals.*

Notations. Throughout this paper, $\mathbb{R}$ (respectively, $\mathbb{N}$) denotes the set of all real numbers (respectively, nonnegative integers). $\mathbb{R}^n$ stands for the set of all real n-dimensional vectors. $\mathbb{R}^{m\times n}$ is the set of all $m \times n$ real matrices. $A > 0$ (respectively, $A \geq 0$) represents a real symmetric positive definite (respectively, positive semi-definite) matrix. M^T and M^{-1} denote the transpose and the inverse of matrix M, respectively. $\mathbb{E}\{x\}$ stands for the mathematical expectation of the stochastic variable x. I is the identity matrix of compatible dimensions and diag$\{\cdots\}$ is a block-diagonal matrix. $\|x\|$ denotes the Euclidean norm of a matrix or vector. $l_2[0, \infty)$ is the space of square summable vectors. The symbol $*$ within a matrix represents the symmetric term of the matrix.

2. Definitions and preliminaries

Consider the following T–S fuzzy system described by

Plant Rule i **:**

IF ζ_{1k} **is** $\mathbb{M}_{i1}$, **and** ζ_{2k} **is** $\mathbb{M}_{i2}$, **and** $\cdots$ **and** ζ_{pk} **is** $\mathbb{M}_{ip}$

$$\textbf{THEN}\ \begin{cases} x_{k+1} = A_i x_k + B_i f_k + C_i v_k + (\bar{A}_i x_k + \bar{C}_i v_k) w_k \\ y_k = D_i x_k + E_i f_k, \quad k \in \mathbb{N} \end{cases} \tag{1}$$

where $x_k \in \mathbb{R}^{n_x}$ is the state vector, $y_k \in \mathbb{R}^{n_y}$ is the measurable output vector, $v_k \in \mathbb{R}^{n_v}$ denotes the exogenous disturbance, $f_k \in \mathbb{R}^{n_f}$ is the fault to be detected, and w_k is a one-dimensional zero-mean Gaussian white noise sequence on a probability space $(\Omega, \mathcal{F}, \text{Prob})$ with $\mathbb{E}\{w_k^2\} = 1$. In addition, v_k and f_k belong to $l_2[0, \infty)$. $i \in \mathbb{S} \triangleq \{1, 2, \ldots, n\}$, where n is the number of IF-THEN rules. $\zeta_{1k}, \zeta_{2k}, \cdots, \zeta_{pk}$ are the premise variables assumed measurable, and $\mathbb{M}_{i1}, \mathbb{M}_{i2}, \cdots, \mathbb{M}_{ip}$ are the fuzzy sets. A_i, B_i C_i, $\bar{A}_i$, $\bar{C}_i$, D_i and E_i are matrices with appropriate dimensions.

In this paper, the event-based mechanism is adopted for the problem of fault detection for T–S fuzzy systems with hope to reduce the frequency of data transfer. Denote the triggering time sequence by $0 \leq k_0 < k_1 < k_2 < \cdots < k_s < \cdots$ and set the generator function $h(\cdot, \cdot, \cdot) : \mathbb{R}^{n_y} \times \mathbb{R}^{n_y} \times \mathbb{R} \to \mathbb{R}$ as follows:

$$h(y_k, y_k^t, \sigma) = (y_k - y_k^t)^T \Theta (y_k - y_k^t) - \sigma y_k^T \Theta y_k \tag{2}$$

where $y_k^t = y_{k_s}$ $(k > k_s)$ is the measurement at the latest triggering time k_s, $\Theta > 0$ is a symmetric positive definite weighting matrix, and $\sigma > 0$ is the threshold. The execution would be triggered as long as the following condition

$$h(y_k, y_k^t, \sigma) > 0 \tag{3}$$

is satisfied. On the other hand, since the communication channel in networked control systems maybe unreliable, the measurement may not be consecutive but contain missing observation. For plant rule i, the measurement signal received by the fault detection filter is described by

$$z_k = \beta_k y_k^t + G_i v_k \tag{4}$$

where v_k is the exogenous disturbance, G_i is a constant matrix, $\beta_k \in \mathbb{R}$ is a random variable taking values of 1 and 0 with $\text{Prob}\{\beta_k = 1\} = \mathbb{E}\{\beta_k\} = \bar{\beta}$, $\text{Prob}\{\beta_k = 0\} = 1 - \bar{\beta}$. Here, $\bar{\beta} \in [0, 1]$ is a known constant. Moreover, one has $\mathbb{E}\{(\bar{\beta} - \beta_k)^2\} = \bar{\beta}(1 - \bar{\beta}) := \tilde{\beta}$.

Consider the following fault detection filter:

Fault detection filter i **:**

IF ζ_{1k} **is** $\mathbb{M}_{i1}$, **and** ζ_{2k} **is** $\mathbb{M}_{i2}$, **and** $\cdots$ **and** ζ_{pk} **is** $\mathbb{M}_{ip}$

$$\textbf{THEN}\ \begin{cases} \hat{x}_{k+1} = A_i \hat{x}_k + K_i (z_k - \bar{\beta} D_i \hat{x}_k) \\ r_k = M(z_k - \bar{\beta} D_i \hat{x}_k) \end{cases} \tag{5}$$

where $\hat{x}_k \in \mathbb{R}^{n_x}$ is the estimated state, $r_k \in \mathbb{R}^{n_r}$ is the residual signal, and K_i, M are the filter parameters to be designed.

The final output of the T–S fuzzy system (1) can be represented in the following form:

$$\begin{cases} x_{k+1} = \sum_{i=1}^{n} \mu_i(\zeta_k) \big\{ A_i x_k + B_i f_k + C_i v_k + (\bar{A}_i x_k + \bar{C}_i v_k) w_k \big\} \\ y_k = \sum_{i=1}^{n} \mu_i(\zeta_k) \{ D_i x_k + E_i f_k \} \end{cases} \tag{6}$$

where $\zeta_k = [\zeta_{1k}, \zeta_{2k}, \ldots, \zeta_{pk}]$ and $\mu_i(\zeta_k) = \frac{\omega_i(\zeta_k)}{\sum_{i=1}^{n} \omega_i(\zeta_k)}$, $\omega_i(\zeta_k) = \prod_{j=1}^{p} \mathbb{M}_{ij}(\zeta_{jk})$ with $\mathbb{M}_{ij}(\zeta_{jk})$ represents the grade of membership of ζ_{jk} in $\mathbb{M}_{ij}$. It is always assumed that $\omega_i(\zeta_k) \geq 0$, $i \in \mathbb{S}$ and $\sum_{i=1}^{n} \omega_i(\zeta_k) > 0$. Then, one has $\mu_i(\zeta_k) \geq 0$, $i \in \mathbb{S}$ and $\sum_{i=1}^{n} \mu_i(\zeta_k) = 1$.

Denoting

$$\begin{aligned} &\big[A(\mu_k)\ B(\mu_k)\ C(\mu_k)\ \bar{A}(\mu_k)\ \bar{C}(\mu_k)\ D(\mu_k)\ E(\mu_k)\ G(\mu_k) \big] \\ &\quad = \sum_{i=1}^{n} \mu_i(\zeta_k) \big[A_i\ B_i\ C_i\ \bar{A}_i\ \bar{C}_i\ D_i\ E_i\ G_i \big], \end{aligned} \tag{7}$$

the system (6) can be rewritten as

$$\begin{cases} x_{k+1} = A(\mu_k) x_k + B(\mu_k) f_k + C(\mu_k) v_k + (\bar{A}(\mu_k) x_k + \bar{C}(\mu_k) v_k) w_k \\ y_k = D(\mu_k) x_k + E(\mu_k) f_k. \end{cases} \tag{8}$$

In the same way, the filter (5) can be written as follows:

$$\begin{cases} \hat{x}_{k+1} = A(\mu_k) \hat{x}_k + K(\mu_k)(z_k - \bar{\beta} D(\mu_k) \hat{x}_k) \\ r_k = M(z_k - \bar{\beta} D(\mu_k) \hat{x}_k) \end{cases} \tag{9}$$

where $K(\mu_k) = \sum_{i=1}^{n} \mu_i(\zeta_k) K_i$.

Setting $\tilde{x}_k = x_k - \hat{x}_k$, $\rho_k = y_k^t - y_k$ and $\hat{\beta}_k = \bar{\beta} - \beta_k$, the error system can be derived from (8) and (9) as follows:

$$\begin{cases} \tilde{x}_{k+1} = A(\mu_k)\tilde{x}_k - \bar{\beta} K(\mu_k) D(\mu_k) \tilde{x}_k + \hat{\beta}_k K(\mu_k) D(\mu_k) x_k - \bar{\beta} K(\mu_k) \rho_k \\ \qquad + \hat{\beta}_k K(\mu_k) \rho_k + (B(\mu_k) - \bar{\beta} K(\mu_k) E(\mu_k)) f_k + \hat{\beta}_k K(\mu_k) E(\mu_k) f_k \\ \qquad + (C(\mu_k) - K(\mu_k) G(\mu_k)) v_k + (\bar{A}(\mu_k) x_k + \bar{C}(\mu_k) v_k) w_k \\ r_k = M(\beta_k D(\mu_k) x_k + \beta_k E(\mu_k) f_k + \beta_k \rho_k + G(\mu_k) v_k - \bar{\beta} D(\mu_k) \hat{x}_k). \end{cases} \tag{10}$$