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Robust Fault Diagnosis Scheme in a Class of Nonlinear System based on UIO and Fuzzy Residual

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Abstract: In this study, a novel robust fault diagnosis scheme is developed for a class of nonlinear systems when both fault and disturbance are considered. The proposed scheme includes both component and sensor fault with nonlinear system that transferred to nonlinear Takagi-Sugeno (T-S) model. It considers a larger category of nonlinear system when fuzzification is used for only nonlinear distribution matrices. In fact the proposed method covers nonlinear systems could not transform to linear T-S model. This paper studies the problem of robust fault diagnosis based on two fuzzy nonlinear observers, the first one is a fuzzy nonlinear unknown input observer (FNUIO) and the other is a fuzzy nonlinear Luenberger observer (FNLO). This approach decouples the faulty subsystem from the rest of the system through a series of transformations. Then, the objective is to design FNUIO to guarantee the asymptotic stability of the error dynamic using the Lyapunov method; meanwhile, FNLO is designed for faulty subsystem to generate fuzzy residual signal based on a quadratic Lyapunov function and some matrices inequality convexification techniques. FNUIO affects only the fault free subsystem and completely removes any unknown inputs such as disturbances when residual signal is generated by FNLO is affected by component or sensor fault. This novelty and using nonlinear system in T-S model make the proposed method extremely effective from last decade literature. Sufficient conditions are established in order to guarantee the convergence of the state estimation error. Thus, a residual generator is determined on the basis of LMI conditions such that the estimation error is completely sensitive to fault vector and insensitive to the unknown inputs. Finally, an numerical example is given to show the highly effectiveness of the proposed fault diagnosis scheme.

Keywords: At least four key words or phrases in alphabetical order, separated by commas.

1. INTRODUCTION

Impermissible deviation a system from standard condition is referred to as a fault. Faulty signals can exist in actuators, sensors and process components of engineering systems that lead to significant performance degradation and even instability of the system. Since fault diagnosis and process monitoring have become an essential part of the modern control systems. The great number of successful fault detection application in industrial processes and automatic control systems help to confirm its necessity, especially in last two decades [1–4].

In the fault diagnosis methods, model-based method could well prove its ability to diagnosis. This can be divided to an analytical model represented by set of differential equations or it can be knowledge-based model represented [4, 5]. Knowledge-based model approaches such as neural networks [6] and experts systems [7] are more suitable for information-poor systems; on the other hand, in analytical model-based approaches, residual signal is generated by using the mathematical model of the system. The most commonly used approaches include Observer-based approach [8, 9], Parity space approach [10] and Parameter estimation-based approach [11]. In general, parity space approach and parameter-based approach are not suitable for nonlinear systems and will not be considered in this paper. Observer-based technique has received much attention to design a fault detection filter or residual signal that includes a threshold to detect the fault. Recent papers in this field have been addressed for a class of nonlinear systems but with parametric uncertainty and a certain class of faults [12, 13], time delayed faults [14], sampled-data systems [15], networked control systems [16, 17] and nonlinear switched stochastic systems [18].

On the other research front, fuzzy logic has attracted a great deal of attention to represent a large class of nonlinear systems in the past few decades [19]. It has been

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well recognized, because of simple using to control many complex nonlinear systems and many related studies have been done by other researchers [20, 21]. To mention a few, in [22] was studied the problem of observer-based robust fault detection for a class of discrete-time nonlinear systems. The system was represented by T-S fuzzy affine dynamic models with norm-bounded uncertainties. The proposed scheme is based on a piecewise quadratic Lyapunov function combined with S-procedure and some matrix inequality convexification techniques. The main innovation of the paper is all the conditions are formulated in the form of linear matrix inequalities despite using linearization of the system around different operating point and minimization its fault not rejection. [23] was presented a common approach for systems described by T-S multiple linear models. The principle of the proposed strategy was to transform the fault diagnosis problem in a simple of L_2 norm minimization by introducing a transfer function. The time delay between fault occurrence and fault accommodation was calculated in [24]; also, the damaging effect on system performance and stability has been investigated. In fact, after detection and isolation of fault, an estimation scheme for single fault was designed that was not very real. [25] was considered development of sliding mode unknown input observer for uncertain T-S model by linearization of the system trajectory around the operating sector of the system. In [26] the problem of fuzzy unknown input observer based fault estimation for discrete-time T-S fuzzy systems was considered and proposed a less conservative FUIO design method by using a finite frequency range technique instead of an entire-frequency method. [27] was concerned a fault detection (FD) problem in finite frequency domain for continuous-time T-S fuzzy systems with sensor faults. Some finite frequency performance indices are initially introduced to measure the fault/reference input sensitivity and disturbance robustness. Furthermore in [28] the membership functions was considered unknown, the linear FD filter designed with fixed gains and to reduce the conservatism of the existing results, a switching mechanism was provided to construct an FD filter with varying gains. Sector nonlinearity method is common way to generate a linear fuzzy set from nonlinear system, and the interest of this method is that the final model exactly represents the original nonlinear model. But this can significantly increase the number of rules; moreover, it leads to complex calculations. Furthermore there are a lot of systems that we can not find suitable sector for linearization of system. In [29–31]fuzzy controller with nonlinear local models was extended which decrease the number of needed rules for representing the nonlinear system. The main innovation of this reduction is less computational burden. Therefore the sector nonlinearity is used only for distribution matrix of nonlinear system and using nonlinear form of the system in this paper and fuzzy analysis is a novelty for this paper and It can consider larger category of nonlinear systems. The problem of simultaneously estimation unknown input and fault in the plant in [32] was considered; although, using the derivative of measurements was a big disadvantage of this method. Using an equivalent output error injection approach in the sliding mode observers was proposed to overcome uncertainties in the systems [33], but it covered only actuator fault. A generalized state space form using linear transformation was employed in [34], such that the augmentation system was a descriptor system for state and fault estimation. This singular formulation provided the possibility for sensor fault estimation and actuator faults from the equivalent output error injection signal with sliding manifold however their LMI's conditions was completely conservative. A prescribed H disturbance attenuation level was integrated into the sliding mode observer design using LMI optimization in [8].

Among of studies, unknown input observers (UIO) was capable to reject the effect of unknown input completely [26, 35, 36]. The recent papers in this field have addressed for the class of nonlinear systems with state unknown inputs and certain fault [37], LMI approach for T-S linear fuzzy model in [38, 39], but for T-S bilinear fuzzy model [40]. Despite numerous works available, based on the authors knowledge LMI formulation for the problem of robust state estimation for fault diagnosis simultaneously was rarely considered. These results were only obtained for ordinary nonlinear systems. This paper addresses the robust state estimation and fault diagnosis for fuzzy nonlinear models.

In this paper, the main innovation is to introduce a robust fuzzy scheme for detection and isolation larger class of faulty nonlinear systems compares to last decade literatures. The novelty does not lead to increase the computation; moreover, fault can be occurred in each subsystem of original system such as sensors and states. Indeed, there is not any restriction on time profile of fault, but these should be norm bounded. It is not restricted because, when the domain of fault is infinitive, fault detection scheme is meaningless. The main idea is using linear transformation and suitable NUIO for generating the residual signal. There are some schemes for this extracting, but using faulty subsystems to generate the residual signal is a new idea. After that, using fault free subsystem and faulty subsystem has been generated residual signal. Using quadratic Lyapunov function to prove the theorem makes simple and effective LMIs for design observers.

The rest of this paper is organized as follows: In the second section, the nonlinear model that is affected by fault is presented. Then new method for fault diagnosis is proposed in the third section; after wards, simulation of the proposed scheme, its ability for industrial system has been demonstrated. A conclusion finishes the paper.

2. PROBLEM FORMULATION AND PRELIMINARIES

Consider the following nonlinear system:

$$\dot{x} = f(x,u) + Fd(t) + \psi(y,u)f_c, \quad (1)$$
$$y = Cx + \lambda(y,u)f_s, \quad (2)$$

where $x \in R^n$ is the state vector, $u \in R^{n_u}$ is the input vector and $y \in R^{n_y}$ represents the system output vector. $f_c \in R^{n_c}$ and $f_s \in R^{n_s}$ are component and sensor fault respectively and $d(t) \in R^{n_d}$ contains the uncertainty and disturbance, called unknown input signal. The nonlinear function $f(x,u)$ is differentiable respect to x and u, then this class of system can be converted to a linear and nonlinear parts as follows [41]:

$$\dot{x} = Ax + Bu + G(x,u) + Fd(t) + \psi(y,u)f_c, \quad (3)$$
$$y = Cx + \lambda(y,u)f_s. \quad (4)$$

where A, B, C and F are real constant with known matrices of appropriate dimensions. The known nonlinear function $G(x,u)$ is Lipschitz [42, 43], with respect to x uniformly for $u \in U$ (U is an admissible control set) with positive Lipschitz constant γ_0

$$\|G(x_1,u) - G(x_2,u)\| \leq \gamma_0 \|x_1 - x_2\|, \quad (5)$$

and $\psi(x,u)$, $\lambda(x,u)$ are nonlinear distribution matrix of component and sensor fault assumed to be full rank and norm bounded with positive constants γ_1 and γ_2 as follow:

$$\|\psi(y,u)\| \leq \gamma_1, \quad \|\lambda(y,u)\| \leq \gamma_2. \quad (6)$$

This modelling strategy will be not restricted for the physical models such as the flight control system or on unmanned underwater vehicle and design control laws to compensate for each input controls that gets an arbitrary deflection angle. The objective of the flight control system is to force the missile to achieve the steering commands developed by the guidance system; therefore, position and speed control of the missile present a real problem for the actuators because of the high level of the system nonlinearity and because of the unknown input signals will be necessary. Each fault or failure in the situations of canard, wings or tail fins of a missile enter with high level nonlinearity in the main state space equations after several mapping of coordination [44, 45].

The number of measurements is more than the number of faults occurs in the system

$$n_s + n_c < n_y, \quad (7)$$

and this assumption is not restricted because it can be overcome by using more than one observer, each observer for a subset of the faults that satisfy assumption (7).

Lemma 1: For any matrices X and Y with appropriate dimensions, the following property holds for any positive scalar ε [46]:

$$X^T Y + Y^T X \leq \varepsilon X^T X + \varepsilon^{-1} Y^T Y. \quad (8)$$

3. PROPOSED FAULT DIAGNOSIS SCHEME

In this section, a fault diagnosis scheme introduces that is suitable for a multivariable nonlinear system. T-S fuzzy models can be used to express high level nonlinearity as a set of local subsystems interpolated by membership functions. This approach has proven to be capable of approximating any smooth nonlinear systems especially distribution matrices of each fault. In the complicated system such as a missile, T-S fuzzy model will have a lot of linear local subsystems that leads more computational time. Therefore, the fuzzy model is produced to overcome nonlinearity in its distribution matrix to handle widespread range of faults in different situations of a complicated system. The proposed fault detection scheme has three parts. At first a T-S fuzzy system to represent model (3)-(4) is used, but each of the local models are nonlinear. In the next part, linear transformation for each local model has been generated in order to decoupling the state and output equations into free and fault dependent parts. Third part covers the fault detection and isolation together when the fault free part is used to design an observer that would guarantee estimation of the entire state vector irrespective of the magnitude and nature of every fault. Also a pure state estimation is used for residual generator signal.

3.1. Fuzzification

Using sector nonlinearity transformation, fault distribution matrix converts to constant matrix and a T-S fuzzy model for the original model (3)-(4) can be obtain under the form:

$$R^i: \; if \;\; \zeta_1(y,u) \;\; is \;\; \chi_1^i, \ldots, \zeta_m(y,u) \;\; is \;\; \chi_m^i, \;\; then$$
$$\begin{aligned} &\dot{x} = Ax + Bu + G(x,u) + Fd(t) + \psi^i f_c, \\ &y = Cx + \lambda^i f_s \quad i = 1, \ldots, r \end{aligned} \quad (9)$$

where R^i denotes the ith fuzzy inference rule, r is the number of fuzzy rules, $\chi_{\bar{m}}^i (\bar{m} = 1, \ldots, m)$ is a fuzzy set, $\zeta(y,u) = [\zeta_1(y,u), \ldots, \zeta_m(y,u)]$ is the premise variable vector. ψ^i and λ^i are constant matrices for each i that represent the component and sensor fault distribution matrices. The nonlinear models in the consequent parts are called local nonlinear models in this paper.

Given $(y(t), u(t))$, the final outputs of nonlinear T-S fuzzy systems are inferred as follows:

$$\dot{x} = \sum_{i=1}^{r} h_i(.)(Ax + Bu + G(x,u) + Fd(t) + \psi^i f_c), \quad (10)$$

$$y = \sum_{i=1}^{r} h_i(.)(Cx + \lambda^i f_s) \quad (11)$$

the weighting functions satisfy the following properties:

$$\sum_{i=1}^{r} h_i(\zeta(y,u)) = 1.$$
$$0 \leqslant h_i(\zeta(y,u)) \leqslant 1, \quad \forall i \in \{1,\cdots,r\}.$$

Given the system (10)-(11) affected by some fault and disturbance, the diagnosis task consists in generating a residual signal that is mainly affected by the fault . In the following subsection, the proposed method using fuzzy nonlinear observer is investigated.

3.2. Decoupling the faulty subsystems

To decouple the rest of the system is affected by the fault in each of the fuzzy subsystems, a linear transformation has been used. The faulty subsystems are completely affected by the fault and thus can be used to make a residual signal. This residual has maximum sensitivity to the fault while insensitive to disturbance in order that the fault diagnosis in robust control; as a result, it can detect each critical condition that faults can make.

In this stage, a linear orthogonal transformation, converts each local model to two subsystems and it can convert each rule of the fuzzy systems. Since rank(ψ^i) = n_c , therefore without loss of generality, there is a nonsingular change of coordinate T_0^i which provides the following geometric condition associated with ψ^i:

$$T_0^i \psi^i = \begin{bmatrix} e^i \\ 0 \end{bmatrix}, \tag{12}$$

where $e^i \in R^{n_c \times n_c}$ and by using T_0^i, matrix F has been partitioned as:

$$T_0^i F = \begin{bmatrix} f_1^i \\ f^i \end{bmatrix} \tag{13}$$

for each nonsingular f_1^i exists a nonsingular transformation T_1^i as:

$$T_1^i = \begin{bmatrix} I_{n_c} & -f_1^i f^{i^{-1}} \\ 0_{n-n_c \times n_c} & I_{n-n_c} \end{bmatrix}, \tag{14}$$

then

$$T_1^i T_0^i \psi^i = \begin{bmatrix} e^i \\ 0 \end{bmatrix}, \quad T_1^i T_0^i F = \begin{bmatrix} 0 \\ f^i \end{bmatrix}.$$

Furthermore λ^i is corresponding distribution matrix with full columns rank and thus without loss of generality, there is a nonsingular transformation S^i which provides the following geometric condition.

$$S^i \lambda^i = \begin{bmatrix} l^i \\ 0 \end{bmatrix}, \tag{15}$$

where $l^i \in R^{n_s \times n_s}$ with rank(l^i) = n_s then the state space equation (9) becomes:

$$\dot{x}_1 = a_1^i x_1 + a_2^i x_2 + b_1^i u + G_1^i(T^{i^{-1}} \bar{x}, u) + e^i f_c, \tag{16}$$

$$\dot{x}_2 = a_3^i x_1 + a_4^i x_2 + b_2^i u + G_2^i(T^{i^{-1}} \bar{x}, u) + f^i d. \tag{17}$$
$$y_1 = c_1^i x_1 + c_2^i x_2 + l^i f_s, \tag{18}$$
$$y_2 = c_3^i x_1 + c_4^i x_2. \tag{19}$$

use these coordinate transformation S^i and $T^i = T_1^i T_0^i$ for each local model

$$\bar{x} := T^i x = T^i \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad \bar{y} = S^i y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}.$$

Thus the state space equation has been decoupled, as shown in (16) - (19). Note that $\dot{x}_2$ and y_2 are not affected by the faults f_c and f_s since rank$(c_3^i) = n_c$, a nonsingular matrix may be constructed from

$$N_2^i = \begin{bmatrix} c_3^{i^+} \\ M_2^i \end{bmatrix}. \tag{20}$$

where, $c_3^{i^+}$ is the pseudo-inverse of c_3^i, defined as $c_3^i = (c_3^{i^T} c_3^i)^{-1} c_3^{i^T}$ and $M_2^i \in R^{(n_y-n_s-n_c)\times(n_y-n_s)}$ is an arbitrarily selected matrix so that N_2^i is nonsingular. Premultiplying fault free part of (18) with N_2^i gives

$$x_1 = c_3^{i^+}(y_2 - c_4^i x_2), \tag{21}$$
$$M_2^i y_2 = M_2^i c_3^i x_1 + M_2^i c_4^i x_2. \tag{22}$$

Substituting (21) into fault free part of (17), (19) and (22) yields

$$\dot{x}_2 = \tilde{A}_2^i x_2 + \tilde{B}_2^i \tilde{u} + G_2^i(T^{i^{-1}} \bar{x}, u) + F_2^i d(t), \tag{23}$$
$$\tilde{y}_2 = \tilde{C}_2^i x_2. \tag{24}$$

Define

$$\tilde{A}_2^i = (a_4^i - a_3^i c_3^{i^+} c_4^i), \tag{25}$$
$$\tilde{B}_2^i = \begin{bmatrix} b_2^i & a_3^i c_3^{i^+} S_2^i \end{bmatrix}, \tag{26}$$
$$\tilde{H}_2^i = M_2^i (I_{n_y-n_s} - c_3^i c_3^{i^+}) S_2^i, \tag{27}$$
$$\tilde{C}_2^i = M_2^i (I_{n_y-n_s} - c_3^i c_3^{i^+}) c_4^i, \tag{28}$$
$$\tilde{y}_2 = \tilde{H}_2^i y, \quad \tilde{u} = [u \quad y]^T, \quad F_2^i = f^i, \tag{29}$$

where S_1^i and S_2^i are first n_s rows and end $n_y - n_s$ rows of coordination matrix S^i.

Then using faulty part of (16) and premultiply with nonsingular matrix as

$$N_1^i = \begin{bmatrix} c_4^{i^+} \\ M_1^i \end{bmatrix}. \tag{30}$$

where, $c_4^{i^+}$ is the pseudo-inverse of c_4^i. If the number of pure states $(n - n_c)$ are more than the number of pure outputs $(n_y - n_s)$ do not need to select any arbitrary matrix M_1^i. With suitable $M_1^i \in R^{(n_y-n_s-n+n_c)\times(n_y-n_s)}$, the following relations by (18) will be established:

$$x_2 = c_4^{i^+}(y_2 - c_3^i x_1), \tag{31}$$

$$M_1^i y_2 = M_1^i c_3^i x_1 + M_1^i c_4^i x_2. \tag{32}$$

substituting (31) into faulty part of (16), (18) and (32) yields

$$\dot{x}_1 = \tilde{A}_1^i x_1^i + \tilde{B}_1^i \tilde{u} + G_1^i(T^{i^{-1}}\bar{x}, u) + E_1^i f_c, \tag{33}$$
$$\tilde{y}_1 = \tilde{C}_1^i x_1 + L_1^i f_s. \tag{34}$$

Define

$$\tilde{A}_1^i = (a_1^i - a_2^i c_4^{i^+} c_3^i), \tag{35}$$
$$\tilde{B}_1^i = \begin{bmatrix} b_1^i & a_2^i c_4^{i^+} S_2^i \end{bmatrix}, \tag{36}$$
$$\tilde{C}_1^i = \begin{bmatrix} (c_1^i - c_2^i c_4^{i^+} c_3^i) \\ M_1^i (I_{n_y - n_s} - c_4^i c_4^{i^+}) c_3^i \end{bmatrix}, \tag{37}$$
$$\tilde{H}_1^i = \begin{bmatrix} (S_1^i - c_2^i c_4^{i^+} S_2^i) \\ M_1^i (I_{n_y - n_s} - c_4^i c_4^{i^+}) S_2^i \end{bmatrix}, \tag{38}$$
$$\tilde{y}_1 = \tilde{H}_1^i y, \quad L_1^i = \begin{bmatrix} l^{i^T} & 0^T \end{bmatrix}^T, \quad E_1^i = e^i. \tag{39}$$

Therefore, subsystems that include all faults in the plant and subsystems that are free from each fault are generated; as a result, the fuzzy system can be represented by:

$$R^i : if\, \zeta_1(y,u) is \chi_1^i, \ldots, \zeta_m(y,u) is \chi_m^i, then$$
$$\begin{cases} \dot{x}_2 = \tilde{A}_2^i x_2 + \tilde{B}_2^i \tilde{u} + G_2^i(T^{i^{-1}}\bar{x}, u) + F_2^i d, \\ \tilde{y}_2 = \tilde{C}_2^i x_2, \end{cases} \tag{40}$$
$$\begin{cases} \dot{x}_1 = \tilde{A}_1^i x_1 + \tilde{B}_1^i \tilde{u} + G_1^i(T^{i^{-1}}\bar{x}, u) + E_1^i f_c, \\ \tilde{y}_1 = \tilde{C}_1^i x_1 + L_1^i f_s. \end{cases} \tag{41}$$

The main reason to require rank(ψ^i) = n_c and rank(λ^i) = n_s is that each fault have affected on corresponding state variables or output signals (41). If these conditions do not preserve in the sector nonlinearity method, corresponding fault can not have suitable effect on the residual signal for fault detection; but, it can be relaxed by choosing larger or smaller subset of sector to overcome full rank condition for each distribution matrix.

3.3. ROBUST RESIDUAL GENERATOR

The residual generator design for nonlinear system described by the faulty subsystem is addressed in this section. At first, an observer for each of the fault free subsections (40) designs and the ith observer rule is of the following form:

$$R^i : if\, \zeta_1(y,u) is \chi_1^i, \ldots, \zeta_m(y,u) is \chi_m^i, then$$
$$\begin{aligned} \dot{z}_2 &= H_2^i z_2 + J_2^i \tilde{u} + W_2^i \tilde{y}_2 + Q_2^i G_2^i(T^{i^{-1}}\hat{\bar{x}}, u), \\ \hat{x}_2 &= z_2 - R_2^i \tilde{y}_2, \\ \hat{x}_1 &= c_3^{i^+}(S_2^i y - c_4^i \hat{x}_2), \end{aligned} \tag{42}$$

where H_2^i, J_2^i, W_2^i, Q_2^i and R_2^i for $i = 1, \ldots, r$ are constant matrices with appropriate dimensions defined as

$$H_2^i = Q_2^i \tilde{A}_2^i - K_2^i \tilde{C}_2^i, \quad Q_2^i = I + R_2^i \tilde{C}_2^i,$$
$$W_2^i = K_2^i - H_2^i R_2^i, \quad J_2^i = Q_2^i \tilde{B}_2^i, \tag{43}$$

but K_2^i and R_2^i are chosen by Preposition 1. $z_2 \in \Re^{n-n_c}$ is the observer state and $\hat{\bar{x}} = [\hat{x}_1 \quad \hat{x}_2]^T$ is the estimated real transformed state vector. The objective is to determine the gains of the observer such that the state estimation error converges towards zero.

Nonlinear unknown input observer (42) has some matrices such as $H_2^i, Q_2^i, W_2^i, J_2^i$ and K_2^i that has been reduced to two matrices K_2^i and R_2^i. Indeed these matrices create relaxed conditions to design a stable observer to compare ordinary observer that has a one design matrix. Sufficient condition for FNUIO (42) is given in the following preposition and outlines a constructive design procedure.

Preposition 1: Given the nonlinear system (3), (4) with assumptions (5)-(6) and Lipschitz constant γ_0, consider FNUIO structure (42)-(43). The observer error dynamics is asymptotically stable such that $\varepsilon > 0$, $\bar{K}_2^i$, $\bar{R}_2^i$, and a positive-definite symmetric matrix P_2 exist such that the following linear conditions hold for $i = 1, \ldots, r$:

$$\begin{pmatrix} X^i & X_{12}^i \\ X_{12}^{i^T} & -\varepsilon^{-1} I \end{pmatrix} < 0, \tag{44}$$
$$(I + \bar{R}_2^i \tilde{C}_2^i) F_2^i = 0, \tag{45}$$

where X^i and X_{12}^i are defined as

$$\begin{aligned} X^i &= ((P_2 + \bar{R}_2^i \tilde{C}_2^i)\tilde{A}_2^i - \bar{K}_2^i \tilde{C}_2^i)^T \\ &\quad + (P_2 + \bar{R}_2^i \tilde{C}_2^i)\tilde{A}_2^i - \bar{K}_2^i \tilde{C}_2^i + \varepsilon^{-1}\gamma_0^2 I, \\ X_{12}^i &= P_2 + \bar{R}_2^i \tilde{C}_2^i, \end{aligned} \tag{46}$$

with $K_2^i = P_2^{-1}\bar{K}_2^i$ and $R_2^i = P_2^{-1}\bar{R}_2^i$.

Proof: During the decoupling of fuzzy nonlinear system the transformed states $e_2 = x_2 - \hat{x}_2$ and $e_1 = x_1 - \hat{x}_1$, satisfy

$$e_2 = \sum_{i=1}^{r} h_i(.)((I + R_2^i \tilde{C}_2^i)x_2 - z_2), \tag{47}$$
$$e_1 = \sum_{i=1}^{r} h_i(.)(-c_3^{i^+} c_4^i e_2), \tag{48}$$

then the equation of the observing error dynamics from (40) and (42) becomes

$$\begin{aligned} \dot{e}_2 = \sum_{i=1}^{r} h_i(.)(H_2^i e_2 + (Q_2^i \tilde{A}_2^i - H_2^i Q_2^i - W_2^i \tilde{C}_2^i)x_2 \\ + (Q_2^i \tilde{B}_2^i - J_2^i)\tilde{u} + Q_2^i \tilde{G}_2^i), \end{aligned} \tag{49}$$

where $Q_2^i = (I + R_2^i \tilde{C}_2^i)$, $K_2^i = W_2^i + H_2^i R_2^i$ and $\tilde{G}_2 = G_2^i(\hat{\bar{x}}, u) - G_2^i(x, u)$. If the following conditions hold true $\forall i = 1, \ldots, r$

$$H_2^i = Q_2^i \tilde{A}_2^i + K_2^i \tilde{C}_2^i, \quad J_2^i = Q_2^i \tilde{B}_2^i, \quad Q_2^i F_2^i = 0.$$

Then the equation of the observing error dynamic becomes

$$\dot{e}_2 = \sum_{i=1}^{r} h_i(\zeta(y,u))(H_2^i e_2 + Q_2^i \tilde{G}_2^i). \tag{50}$$

Let us consider the following Lyapunov function

$$V(e_2(t)) = e_2^T(t) P_2 e_2(t). \tag{51}$$

Using (51), the derivative of the Lyapunov function is given by

$$\dot{V}(e_2) = \sum_{i=1}^{r} h_i(.)(e_2^T(H_2^{i^T} P_2 + P_2 H_2^i)e_2 + 2e_2^T P_2 Q_2^i \tilde{G}_2^i)$$

using Lemma 1 and (5),

$$\dot{V}(e_2) \leq \sum_{i=1}^{r} h_i(.)(e_2^T(H_2^{i^T} P_2 + P_2 H_2^i + \varepsilon P_2 Q_2^{i^T} Q_2^i P_2 + \varepsilon^{-1}\gamma_0^2 I)e_2). \tag{52}$$

Stability condition for the estimation error yields to that the time derivative of the Lyapunov function should be negative define.

$$H_2^{i^T} P_2 + P_2 H_2^i + \varepsilon P_2 Q_2^{i^T} Q_2^i P_2 + \varepsilon^{-1}\gamma_0^2 I < 0. \tag{53}$$

While replacing H_2^i and Q_2^i, then using the variable change $\bar{R}_2^i = P_2 R_2^i$ and $\bar{K}_2^i = P_2 K_2^i$, the last inequality (54) can be written such that

$$((P_2 + \bar{R}_2^i \tilde{C}_2^i)\tilde{A}_2^i - \bar{K}_2^i \tilde{C}_2^i)^T + (P_2 + \bar{R}_2^i \tilde{C}_2^i)\tilde{A}_2^i - \bar{K}_2^i \tilde{C}_2^i + \varepsilon(P_2 + \bar{R}_2^i \tilde{C}_2^i)(P_2 + \bar{R}_2^i \tilde{C}_2^i)^T + \varepsilon^{-1}\gamma_0^2 I < 0. \tag{54}$$

By using the Schur complement on inequality (54), LMI (44) with parameters of (46) concludes . □

Moreover an observer for each of the faulty subsections (41) designs. This Observer is inferred as follows:

$$\begin{aligned} &R^i : if\, \zeta_1(y,u) is \chi_1^i, \ldots, \zeta_m(y,u) is \chi_m^i, then \\ &\quad \dot{\hat{\hat{x}}}_1 = \tilde{A}_1^i \hat{\hat{x}}_1 + \tilde{B}_1^i \tilde{u} + G_1^i(\hat{\hat{x}},u) + N^i(\tilde{y}_1 - \tilde{C}_1^i \hat{\hat{x}}_1), \\ &\quad \hat{\hat{y}}_1 = \tilde{C}_1^i \hat{\hat{x}}_1, \\ &\quad r_x = \hat{x}_1 - \hat{\hat{x}}_1, \\ &\quad r_y = \tilde{y}_1 - \hat{\hat{y}}_1, \end{aligned} \tag{55}$$

where N_1^i for $i = 1, \ldots, r$ is constant matrix with appropriate dimensions and it is chosen according to the following theorem. $\hat{\hat{x}}_1 \in \Re^{n_c}$ is the estimated state vector from faulty subsystem. Because of omitting disturbance in faulty subsystems, $\hat{\hat{x}}_1$ has affected by only fault. Sufficient condition for guaranteeing the asymptotic convergence of state estimation error in the residual signals r_x and r_y is in the following theorem.

Theorem 1: The residual generator (55) converges asymptotically to the state of the fuzzy model (41), if the fault is bounded, and if $\varepsilon > 0$, $\bar{\varepsilon} > 0$, N_1^i for $i = 1, \ldots, r$, and a positive-definite symmetric matrix P_1 exist such that the following LMI optimization problem has a solution

$$\begin{pmatrix} Z^i & P_1 \\ P_1 & -\varepsilon^{-1} I \end{pmatrix} < 0, \tag{56}$$

$$Z^i = (\tilde{A}_1^{i^T} P_1 + P_1 \tilde{A}_1^{i^T} - \tilde{C}_1^{i^T} \bar{N}_1^{i^T} - \bar{N}_1^i \tilde{C}_1^i + \bar{\varepsilon}^{-1}\gamma^2) \tag{57}$$

with $N_1^i = P_1^{-1} \bar{N}_1^i$.

Proof: The residual signals can be rewritten as,

$$r_x = x_1 - \hat{\hat{x}}_1 + \sum_{i=1}^{r} h_i(.) c_3^{i^+} c_4^i e_2, \tag{58}$$

$$r_y = \sum_{i=1}^{r} h_i(.) \tilde{C}_1^i (x_1 - \hat{\hat{x}}_1) \tag{59}$$

in the Preposition 1 is concluded e_2 converges toward zero therefore it can remove from (58). Then the equation of the observing error dynamics from (41) and (55) becomes

$$\dot{r}_x = \sum_{i=1}^{r} h_i(.)((\tilde{A}_1^i - N_1^i \tilde{C}_1^i) r_x + \tilde{G}_1^i + E_1^i f_c - N_1^i L_1^i f_s), \tag{60}$$

where $\tilde{G}_1 = G_1^i(T^i \hat{\hat{x}}, u) - G_1^i(T^i \bar{x}, u)$. Let us consider the following Lyapunov function

$$V(r_x(t)) = r_x^T(t) P_1 r_x(t). \tag{61}$$

Using (60), the derivative of the Lyapunov function is given by

$$\dot{V}(r_x(t)) = \sum_{i=1}^{r} h_i(.)(r_x^T((\tilde{A}_1^i - N_1^i \tilde{C}_1^i) P_1 + P_1(\tilde{A}_1^i - N_1^i \tilde{C}_1^i) r_x + 2r_x^T P_1 \tilde{G}_1^i + 2r_x^T P_1 (E_1^i f_c - N_1^i L_1^i f_s)). \tag{62}$$

Using Lemma 1, (5) and upper bound ρ on faulty part,

$$\dot{V}(r_x(t)) \leq \sum_{i=1}^{r} h_i(.) r_x^T (\tilde{A}_1^{i^T} P_1 + P_1 \tilde{A}_1^i - \tilde{C}_1^{i^T} N_1^{i^T} - N_1^i \tilde{C}_1^i n + \varepsilon_1 P_1 P_1 + \varepsilon_1^{-1}\gamma^2 + \varepsilon_2 P_1 P_1 \rho^2 + \varepsilon_2^{-1} I) r_x. \tag{63}$$

Stability condition for the estimation error yields to that the time derivative of the Lyapunov function should be negative define.

$$\tilde{A}_1^{i^T} P_1 + P_1 \tilde{A}_1^i - \tilde{C}_1^{i^T} N_1^{i^T} - N_1^i \tilde{C}_1^i + (\varepsilon_1 + \varepsilon_2 \rho^2) P_1 P_1 + (\varepsilon_1^{-1}\gamma^2 + \varepsilon_2^{-1}) I < 0 \tag{64}$$

by changing define $\varepsilon = \varepsilon_1 + \varepsilon_2 \rho^2$, $\bar{\varepsilon} = \varepsilon_1^{-1}\gamma^2 + \varepsilon_2^{-1}$ and using the variable change $\bar{N}_1^i = P_1 N_1^i$ and by using the Schur complement on inequality (64), LMI (56) concludes . □

Faulty subsystem has n_c state and its distribution matrix is full rank, so each of the component faults correspond to its state and this concept is common on the outputs of faulty subsystem. Consequently fault isolation has done with fault detection simultaneously. These observers are able to remove all disturbance and uncertainty.

4. SIMULATION RESULTS

In this section, an example is given to illustrate the performance of proposed method. Assume that the nonlinear model can be affected by a disturbance and fault. Consider nonlinear model with the following equations:

$$\begin{aligned}
\dot{x}_1 &= -6x_1 - x_2 + u + x_3 \sin x_1 + d(t), \\
\dot{x}_2 &= 5x_1 - x_2 + u + x_1 x_2, \\
\dot{x}_3 &= x_2 - 2x_3 + u + x_2 u + x_2 \sin x_3 + d(t), \\
y_1 &= 0.2x_1 - x_2, \\
y_2 &= -0.1x_2 + x_3, \\
y_3 &= 0.1x_1 - x_3.
\end{aligned} \tag{65}$$

At first, the Lipschitz constant is computed and this is computed as supremum of the magnitude of the partial derivative of the nonlinear term $G(x,u)$. That is

$$\gamma_0 = \| \frac{\partial G(x,u)}{\partial x} \|_\infty ,$$

where x,u are belong to domain of the nonlinear system under consideration and

$$G(x,u) = \begin{bmatrix} x_3 \sin x_1 \\ x_1 x_2 \\ x_2 u + x_2 \sin x_3 \end{bmatrix}$$

for this example the Lipschitz constant is computed as $\gamma_0 = 1$.

The nonlinear system beside the disturbance has two faults. Based on the situation of the faults, these can occur in three sections such as two component faults, two sensor faults or one component and one sensor fault. In this section last situation is considered that includes two different type of faults.

The previous nonlinear model (65) can be rewritten as

$$\begin{aligned}
\dot{x} &= Ax + Bu + G(x,u) + Fd(t) + \psi(y,u) f_c(t), \\
y &= Cx + \lambda(y,u) f_s(t),
\end{aligned}$$

where the matrices $\psi(.)$ and $\lambda(.)$ contain two nonlinear continuous terms $z_1(y,u) = y_1 y_2$, $z_2(y,u) = 0.5 y_1 y_3$.

$$\psi = \begin{bmatrix} y_1 y_2 \\ 1 \\ 1 \end{bmatrix}, \quad \lambda = \begin{bmatrix} 0.5 y_1 y_3 \\ 1 \\ 1 \end{bmatrix}.$$

z_1 and z_2 are two premise variables depend on state measurements. Each premise variable is bounded in a compact state space:

$$z_1 \in [-0.614, 0], \quad z_2 \in [-0.3155, 0.4422].$$

Using the polytopic transformation of sector nonlinearity method, the nonlinear continuous terms can be written as:

$$\begin{aligned}
z_1(y,u) &= M^1_{F_1}.\bar{z}_1 + M^2_{F_1} \underline{z}_1, \\
z_2(y,u) &= M^1_{F_2}.\bar{z}_2 + M^2_{F_2} \underline{z}_2
\end{aligned}$$

where the functions $M^1_{F_1}, M^2_{F_1}, M^1_{F_2}$ and $M^2_{F_2}$ are respectively given by:

$$\begin{aligned}
M^1_{F_1} &= \frac{\bar{z}_1 - z_1}{\bar{z}_1 - \underline{z}_1}, \qquad M^2_{F_1} = \frac{z_1 - \underline{z}_1}{\bar{z}_1 - \underline{z}_1}, \\
M^1_{F_2} &= \frac{\bar{z}_2 - z_2}{\bar{z}_2 - \underline{z}_2}, \qquad M^2_{F_2} = \frac{z_2 - \underline{z}_2}{\bar{z}_2 - \underline{z}_2}.
\end{aligned} \tag{66}$$

The fuzzy nonlinear model is obtained by an interpolation of local models with four membership functions (66), and for each subsystem, there are two transformations T,S to convert system to two subsystems:

$$\begin{aligned}
T_1 &= \begin{bmatrix} -0.7071 & 0 & 0.7071 \\ 0.6196 & 1 & -.06196 \\ -0.8762 & 0 & -0.5380 \end{bmatrix}, \\
T_2 &= \begin{bmatrix} -0.7071 & 0 & 0.7071 \\ 0.6196 & 1 & -.06196 \\ -0.8762 & 0 & -0.5380 \end{bmatrix}, \\
T_3 &= \begin{bmatrix} -0.7071 & 0 & 0.7071 \\ 1 & 1 & -1 \\ -1.4142 & 0 & 0 \end{bmatrix}, \\
T_4 &= \begin{bmatrix} -0.7071 & 0 & 0.7071 \\ 1 & 1 & -1 \\ -1.4142 & 0 & 0 \end{bmatrix}, \\
S_i &= I_3 \qquad \forall i = 1,2,3.
\end{aligned}$$

The UIO observer gains (43) proposed in this paper for fault free subsystem (40), are obtained by solving the LMI (44) under constrain (45). By choosing the scalar $\varepsilon = 1$, their obtained UIO observer gains are

$$\begin{aligned}
Q^1_2 &= \begin{bmatrix} 1 & 0 \\ 0.0386 & 0 \end{bmatrix}, \quad R^1_2 = \begin{bmatrix} 0 \\ 0.1916 \end{bmatrix}, \\
Q^2_2 &= \begin{bmatrix} 1 & 0 \\ 0.0386 & 0 \end{bmatrix}, \quad R^2_2 = \begin{bmatrix} 0 \\ 0.1916 \end{bmatrix}, \\
Q^3_2 &= \begin{bmatrix} 1 & 0 \\ 0.1768 & 0 \end{bmatrix}, \quad R^3_2 = \begin{bmatrix} 0 \\ 662.135 \end{bmatrix}, \\
Q^4_2 &= \begin{bmatrix} 1 & 0 \\ 0.1768 & 0 \end{bmatrix}, \quad R^4_2 = \begin{bmatrix} 0 \\ 662.135 \end{bmatrix}, \\
K^1_2 &= \begin{bmatrix} 0.6514 \\ -0.1401 \end{bmatrix}, \quad W^1_2 = \begin{bmatrix} 0.7637 \\ 0.0295 \end{bmatrix}, \\
K^2_2 &= \begin{bmatrix} 0.6514 \\ -0.1401 \end{bmatrix}, \quad W^2_2 = \begin{bmatrix} 0.7637 \\ 0.0295 \end{bmatrix}, \\
K^3_2 &= \begin{bmatrix} 1312 \\ -283 \end{bmatrix}, \quad W^3_2 = \begin{bmatrix} 1218 \\ 215 \end{bmatrix}, \\
K^4_2 &= \begin{bmatrix} 1312 \\ -283 \end{bmatrix}, \quad W^4_2 = \begin{bmatrix} 1218 \\ 215 \end{bmatrix},
\end{aligned}$$

$$H_2^1 = \begin{bmatrix} -2.5382 & -0.5864 \\ -0.0647 & 0.7527 \end{bmatrix},$$
$$H_2^2 = \begin{bmatrix} -2.5382 & -0.5864 \\ -0.0647 & 0.7527 \end{bmatrix},$$
$$H_2^3 = \begin{bmatrix} -3.4 & 0.1415 \\ -0.4636 & 0.7527 \end{bmatrix},$$
$$H_2^4 = \begin{bmatrix} -3.4 & 0.1415 \\ -0.4636 & 0.7527 \end{bmatrix},$$
$$J_2^1 = \begin{bmatrix} -0.6196 & 0 & -1.6774 & -0.7195 \\ 0.0239 & 0 & -0.0648 & -0.0278 \end{bmatrix},$$
$$J_2^2 = \begin{bmatrix} -0.6196 & 0 & -1.6774 & -0.7195 \\ 0.0239 & 0 & -0.0648 & -0.0278 \end{bmatrix},$$
$$J_2^3 = \begin{bmatrix} 1 & 0 & -0.4972 & -0.5525 \\ 0.1768 & 0 & -0.0879 & -0.0977 \end{bmatrix},$$
$$J_2^4 = \begin{bmatrix} 1 & 0 & -0.4972 & -0.5525 \\ 0.1768 & 0 & -0.0879 & -0.0977 \end{bmatrix},$$
$$P_2 = \begin{bmatrix} 1.6232 & -0.6426 \\ -0.6426 & 7.1209 \end{bmatrix}.$$

And a nonlinear Lunberger observer gains, same as proposed in Theorem 1, but for fault free subsystems

$$N^1 = \begin{bmatrix} 0.7813 \\ 0.0560 \end{bmatrix}, \qquad N^2 = \begin{bmatrix} 0.7813 \\ 0.0560 \end{bmatrix},$$
$$N^3 = \begin{bmatrix} 650 \\ -514 \end{bmatrix}, \qquad N^4 = \begin{bmatrix} 650 \\ -514 \end{bmatrix},$$
$$P = \begin{bmatrix} 2.5040 & 0.0353 \\ 0.0353 & 1.4110 \end{bmatrix}.$$

The simulation results are presented in Figs. 1-3. Fig. 1 shows unknown input signal and two component faults. Also, residual signals are generated by a fuzzy Lunberger observer (55) for faulty subsystem (41). By choosing the scalers $\varepsilon = 1$ and $\bar{\varepsilon} = 1$, their observer gains obtained simplicity:

$$N_1^i = -1.6645 \qquad \forall i = 1,2,3,4, \qquad P_1 = 1.476.$$

The residual signal response in presence of unknown input signal is shown in Fig. 2. UIO removes effects of unknown input signal completely, but Lunberger observer is sensitive to unknown input signal, same as faults. Fig. 3 display good response of both schemes in absent of unknown signal. Figs. 2 and 3 represent the convergence of the residual corresponding to the fault signals. UIO can remove effect of each unknown input signal, but Lunberger observer can not do it. Simulation results are shown the effectiveness of proposed method to detect every fault in any situation of the plant.

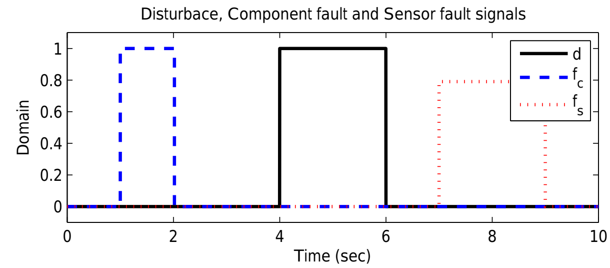

Fig. 1. Unknown input signal(solid line), component fault(dashed line) and sensor fault(dotted line).

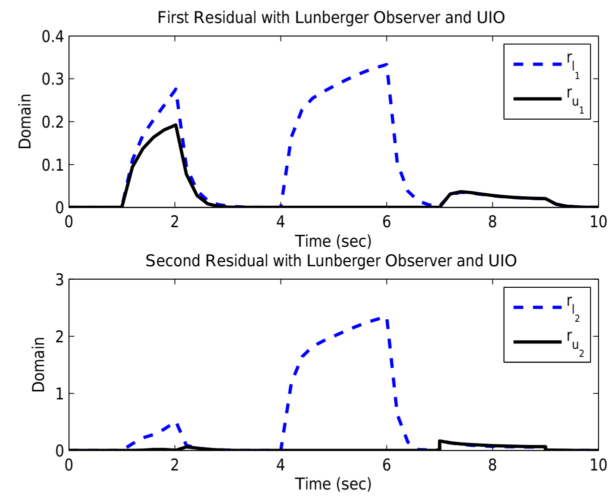

Fig. 2. Residual signals from UIO (solid line) and Lunberger observer (dashed line) under unknown input signal.

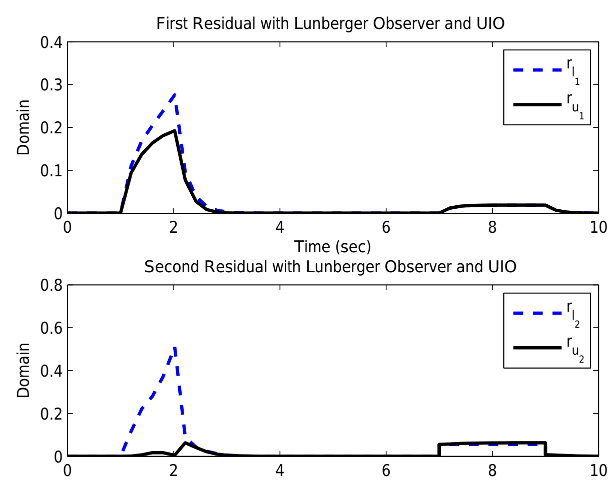

Fig. 3. Residual signals from UIO (solid line) and Lunberger observer (dashed line) without unknown input signal.

5. CONCLUSION

A new scheme for design of fuzzy residual generator for a class of nonlinear systems is presented in this paper. It is shown that the scheme is able to detect the occurrence of faults and eliminate unknown inputs. The considered system are modelled with a T-S fuzzy nonlinear structure.

The proposed results are developed for three cases: component faults, sensor faults and components and sensor faults simultaneously. A stability analysis is carried out using a Lyapunov function. Furthermore, residual signals of proposed approach compare with Lunberger observer based scheme. UIO scheme residuals tracked fault signals in presence of any unknown input signal, but Lunberger based residual could not do it. Indeed a residual generator is considered in order to be sensitive to fault and insensitive to the disturbance or any unknown input signals. Finally, the effectiveness of the technique is illustrated with the help of three numerical examples.

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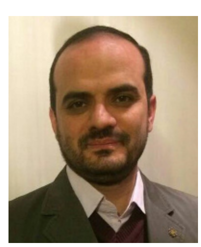

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