Assessment of observer based fault estimators for TS fuzzy models

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Keywords
Observers, Actuators, Fault detection, Nonlinear systems, Robustness, Noise measurement
Assessment of Observer Based Fault Estimators for TS Fuzzy Models

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Keywords - observers; TS fuzzy models; actuator; sensor faults; noise

I. INTRODUCTION

Any unacceptable deviation of system parameters from their nominal values, that may be a sign of near future complete failure, is called fault. Naturally, all processes are vulnerable to faults, therefore, maintaining long run system performance in the form of product quality and or behavior demands certain measures that can be accomplished by automatic fault diagnosis and isolation (FDI) to give early warning and to ensure safety and quality of operations.

Among a few fault diagnosis approaches, the quantitative model based techniques and in particular the observer based method continues to gain an increasing attention in the fundamental and applied research fields [1]. The methods embark on analytical, rather than, measurement redundancies. In practice, due to model uncertainties, disturbances, perturbations and noises, accurate fault estimation, such as the fault size and shape, is a very challenging procedure [2-4].

Most nonlinear behavior systems can be appropriately approximated by Takagi-Sugeno (TS) fuzzy models [5]. Therefore, the problem of fault detection in nonlinear systems is transformed to the fault analysis of TS fuzzy system models. In this respect, plenty of researches have been conducted. A proportional integral (PI) observers has been introduced in [6-8], which detects and estimates the size of actuator faults. The algorithms performance degrades in case of measurement noise [4]. Another technique for actuator fault estimation for T-S fuzzy model has been reported in [9, 10]. Estimation of actuator and sensor faults is the subject of study in [11], where the faults are introduced as auxiliary variables to be estimated. A revised version of PI observer for the detection of sensor and actuator faults has been detailed in [12]. Design of a reduced order robust observer with unknown input for estimation of faults in continuous and discrete TS models has been investigated in [13].

In this paper, the problem of state estimation and actuator/sensor fault detection in a noisy environment of a two-tank system is investigated. The algorithms are the PI observer (PIO) [14] and the robust observer (RO) [4]. It is exhibited that both algorithms operate well in estimating the state and sensor fault; however, contrasts’ are recorded in the detection of the actuator faults. PIO quickly tracks the actuator fault as soon as it occurs but the estimate is noisy, whiles low speed fault tracking RO yields lower variance estimate, which is demanded.

In section 2, the general TS fuzzy model and PIO and RO observer based fault detection algorithms are introduced. In section 3, the simulation results in detecting actuator and sensor faults in a two tank system is investigated and lastly conclusion comes in section 4.

II. TS FUZZY MODEL FAULT DETECTION

A. TS Fuzzy model

Most nonlinear physical systems can be accurately modeled by Takagi-Sugeno (TS) fuzzy systems [5]. The TS fuzzy set approximates a nonlinear system by a combination of several linear local dynamics where each is represented by one of the fuzzy implications. Thus, the global behavior is obtained by the contribution of each of the linear sub-models. It is argued that if nonlinear state system variables are used as the fuzzy decision variables, the fuzzy model is capable of replicating a large class of nonlinear systems [15]. Thus, it is worthwhile to exploit observer based fault detection on these models which it would be applicable to many nonlinear systems [16].

A TS Fuzzy model subject to actuator fault, sensor faults, and unknown disturbance is expressed by,

$$
\begin{align*}
\dot{x}(t) &= \sum_{i=1}^{c} \mu_i (A_i x(t) + B_i u(t) + F_i f_a(t) + H_i w(t)) \\
y(t) &= C x(t) + F f_a(t)
\end{align*}
$$

where \(x(t)\in\mathbb{R}^n\) is the state, \(u(t)\in\mathbb{R}^p\) is the input vector, \(w(t)\in\mathbb{R}^d\).
is the exogenous disturbance, \( y(t) \in \mathbb{R}^m \) is the measured output, \( f_i(t) \in \mathbb{R}^p \) is the actuator and \( f_i(t) \in \mathbb{R}^m \) is the sensor faults. \( A_s, B_s, F_s, C, F, D \) and \( H_i \) are constant real matrices of appropriate dimensions. The \( \mu(x) \) is a membership function of the state variables, \( x \). It is defined by,

\[
\begin{align*}
\sum_{i=1}^{r} \mu_i(x) &= 1 \quad \forall t \geq 0 \\
0 \leq \mu_i(x) &\leq 1 \quad \forall i \in \{1, \ldots, r\}
\end{align*}
\]

Where "r" represents the local models index.

**B. PI observer (PIO) design**

To estimate the states and faults of (1), first, the output is filtered by a stable matrix

\[
\hat{y}_f = -T(y_f - y(t))
\]

and (1) is reformulated by introducing a new state variable, \( r(t) \) as follows [14],

\[
\begin{align*}
\dot{r}(t) &= \sum_{i=1}^{r} \mu_i(A_s r(t) + B_s u(t) + F_s f_i(t) + H_i w(t)) \\
\dot{q}(t) &= C_s r(t)
\end{align*}
\]

\[
\begin{align*}
\dot{r}(t) &= \sum_{i=1}^{r} \mu_i(A_s r(t) + B_s u(t) + F_s f_i(t) + H_i w(t)) \\
\dot{q}(t) &= C_s r(t)
\end{align*}
\]

(4)

Where the matrices \( F_{ii} \) are full column rank. If it is assumed that the fault is in polynomial form of \( k \)-1 degree and their \( k^\text{th} \) derivatives are bounded, i.e. it obeys the following model,

\[
\begin{align*}
\dot{j}(t) &= f_i(t) \\
\dot{f}_s(t) &= f_i(t) \\
\dot{f}_s(t) &\leq f_0
\end{align*}
\]

A proportional integral observer is set up to estimate the states \( x, y_i \) and the fault and its derivatives as given below,

\[
\begin{align*}
\dot{\hat{x}}(t) &= \sum_{i=1}^{r} \mu_i(\dot{i}(t)A_i \hat{i}(t) + B_i u(t) + F_i \hat{j}(t) + K_i \mu_i(q(t) - \hat{q}(t))) + g_i(t) \\
\dot{\hat{q}}(t) &= C_i A_i \hat{i}(t) \\
\dot{\hat{j}}(t) &= \sum_{i=1}^{r} \mu_i(\dot{j}(t)K_i \mu_i(q(t) - \hat{q}(t)) + \hat{j}(t) + g_i(t)) \\
\dot{\hat{j}}(t) &= \sum_{i=1}^{r} \mu_i(\dot{j}(t)K_i \mu_i(q(t) - \hat{q}(t)) + \hat{j}(t) + g_i(t)) \quad \text{for } j = 1 \ldots k = 1
\end{align*}
\]

Where \( K_{pi}, K_a \) and \( K_{bi} \) are the proportional and integral gains, respectively. The variables \( g_i(t) \) and \( g_i(t) \) are introduced in order to compensate the influence of the unmeasurable decision variables. For a matter of simplicity, the system (4) and the observer (6) is restructured to the following compact form,

\[
\begin{align*}
\dot{\hat{x}}(t) &= \sum_{i=1}^{r} \mu_i(A_i \hat{x}(t) + B_i u(t) + \hat{f}_s(t) + H_i w(t)) + J \cdot \hat{f}_s(t) \\
\dot{\hat{q}}(t) &= C_s \hat{x}(t) \\
\dot{\hat{j}}(t) &= \sum_{i=1}^{r} \mu_i(A_i \hat{j}(t) + B_i u(t) + K_i (\hat{q}(t) - \hat{q}(t))) + g(t) \\
\dot{\hat{q}}(t) &= C_s \hat{j}(t)
\end{align*}
\]

Where

\[
\begin{align*}
\dot{r}(t) &= \begin{bmatrix} r(t) \\ f(t) \\ f(t) \\ f_i(t) \\ f_i(t) \\ f_i(t) \end{bmatrix}, \quad \dot{\hat{r}}(t) = \begin{bmatrix} \hat{r}(t) \\ \hat{f}(t) \\ \hat{f}(t) \\ \hat{f}(t) \end{bmatrix}, \quad \dot{g}(t) = \begin{bmatrix} g(t) \\ g(t) \end{bmatrix}, \quad \dot{J}(t) = \begin{bmatrix} J(t) \\ J(t) \end{bmatrix} \\
H_u &= \begin{bmatrix} A_s & F_s & 0 & 0 & \cdots & 0 \\ 0 & 0 & I_n & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & I_n \end{bmatrix}, \quad B_s = \begin{bmatrix} B_1 \\ 0 \end{bmatrix} \\
K &= \begin{bmatrix} K_{pi} \\ K_a \\ K_{bi} \\ K_i \\ C_i \end{bmatrix}
\end{align*}
\]

(8)

Where \( n_f \) is the number of each fuzzy implication is given by,

The observer estimation error,

\[
\varepsilon(t) = r(t) - \hat{r}(t) \quad e_i(t) = \hat{q}(t) - \hat{q}(t)
\]

Is expressed by,

\[
\begin{align*}
\varepsilon(t) &= \sum_{i=1}^{r} \mu_i(\overline{\varepsilon}(t) + G \varepsilon(t) + \Delta \varepsilon(t) - g(t)) \\
\overline{\varepsilon} &= A_s \overline{\varepsilon} + K_s r(t) + G_s \overline{\varepsilon} + K_s I_s \Delta \varepsilon(t) + g(t)
\end{align*}
\]

(10)

The estimation error \( \overline{\varepsilon}(t) \) asymptotically stable and \( L_2 \) stability is guaranteed [14], if there exist a matrix \( P > 0 \), matrices \( N_f > 0 \) and the positive scalars \( \lambda > 0 \) and \( \lambda \) for each fuzzy implication that satisfies the following LMI condition under minimized \( \mu \),

\[
\begin{align*}
\phi &= \begin{bmatrix} \phi_{PI} & \phi_{PH} & P & \delta & J & I \end{bmatrix} & \begin{bmatrix} -\mu I & \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} \end{bmatrix} & < 0 \\
\phi &= \begin{bmatrix} \phi_{PI} & \phi_{PH} & P & \delta & J & I \end{bmatrix} & \begin{bmatrix} -\mu I & \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} \end{bmatrix} & < 0
\end{align*}
\]

(11)

Due to \( \varepsilon(t) \), \( z(t) \) and \( g(t) \) some resides remain on the estimation as (10) indicates. The gain of the PI observer for each fuzzy implication is given by,
\[ K_i = P^{-1}N_i \] (12)

**C. Robust statefault observer (RO)**

By introducing a new state variable \( x \) from the series of \( x \) and the sensor fault \( f_s \), a new arrangement for TS fuzzy model (1) is derived which is expressed by [4],

\[
\begin{align*}
\dot{q}(t) = & \sum \mu_i(A_i x(t) + B_i u(t) + F_i f_s(t) + H_i w(t) + E_i f_f(t)) \\
\bar{x}(t) = & C_i \tilde{e}(t) \\
\tilde{e}(t) = & (x'(t), f_s'(t), y'(t))^T, Q = \begin{bmatrix} I & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & F \end{bmatrix}
\end{align*}
\]

Adding \( K_{iH} \bar{y} \) to both sides of (13) yields,

\[
\begin{align*}
\dot{r}(t) = & \sum \mu_i(A_i r(t) + B_i u(t) + F_i f_f(t) + H_i w(t) + E_i f_f(t) + G_i K_i y(t)) \\
\bar{x}(t) = & C_i \tilde{e}(t) + C_i r(t) + F_i f_f(t) \\
\tilde{e}(t) = & (x'(t), f_f'(t), y'(t))^T, Q = \begin{bmatrix} I & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & F \end{bmatrix}
\end{align*}
\]

It is shown [4] that under the defined conditions, there is a transformation matrix, \( T \) that transforms (14) to the following equation,

\[
T = \left[ C_i^{-1} \right], \bar{x}(t) = T \tilde{e}(t) \]

Adding \( K_{iH} \bar{y} \) to both sides of (14) yields,

\[
\begin{align*}
\dot{r}(t) = & \sum \mu_i(A_i r(t) + B_i u(t) + F_i f_f(t) + H_i w(t) + E_i f_f(t) + G_i K_i y(t)) \\
\bar{x}(t) = & C_i \tilde{e}(t) + C_i r(t) + F_i f_f(t) \\
\tilde{e}(t) = & (x'(t), f_f'(t), y'(t))^T, Q = \begin{bmatrix} I & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & F \end{bmatrix}
\end{align*}
\]

Now, system (15) is decomposed into two sets of variables, variables dependent and independent of the measured \( y \) as follows,

\[
\begin{align*}
\dot{r}(t) = & \sum \mu_i(A_i r(t) + B_i u(t) + F_i f_f(t) + H_i w(t) + E_i f_f(t) + G_i K_i y(t)) \\
\dot{r}_2(t) = & \sum \mu_i(A_i r(t) + B_i u(t) + F_i f_f(t) + H_i w(t) + E_i f_f(t) + G_i K_i y(t)) \\
y(t) = & C_i \tilde{e}(t) + (0 \omega, 0, -1)^T \\
\text{with} \ r_2 \text{ has already been measured, thus the unmeasured} \ r_1 \text{ is required to be estimated. By considering the following equations for} \ f_s, \\
\bar{x} = \begin{bmatrix} x \\ f_s \end{bmatrix} = \begin{bmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{bmatrix} \begin{bmatrix} r_1 \\ r_2 \end{bmatrix} \Rightarrow f_s = T_{21} r_1 + T_{22} r_2
\end{align*}
\]

a reduced order estimator is designed for \( r_1 \) and \( f_s \) as follows [4],

\[
\begin{align*}
\dot{f}_s(t) + & \sum \mu_i(\bar{N}_i + K_n - K_n N_i) y(t) \\
\dot{f}_s(t) + & \sum \mu_i(\bar{N}_i + K_n - K_n N_i) y(t) \\
\dot{f}_s(t) + & \sum \mu_i(\bar{N}_i + K_n - K_n N_i) y(t) \\
y(t) + & \sum \mu_i(\bar{N}_i + K_n - K_n N_i) y(t)
\end{align*}
\] (18)

The observer estimation error is denoted by,

\[
e(t) = [r_1(t) - \bar{r}_1(t)]^T, (f_1(t) - \bar{f}_1(t))^T
\]

It is shown [4] that If there exist a symmetric positive-definite matrix \( P \), and matrices \( M_i > 0 \) (for each fuzzy implication) and \( j = 1, 2 \ldots g \) that satisfies the following linear matrix inequalities,

\[
G_j < 0, \quad \frac{2}{g-1} G_j + G_j + G_j < 0, \quad 1 \leq i \neq j \leq g
\]

Where

\[
G_j = \begin{bmatrix} A_i^T P + P A_i - J_i \bar{M}^T - \bar{M} J_i + M_i \quad PH_i \quad P \end{bmatrix} \\
A_i = \begin{bmatrix} \bar{A}_{ii} & F_{ii} \\ 0 & 0 \end{bmatrix}, \quad J_i = [\bar{A}_{i1}, B_{i2}], \quad H_i = \begin{bmatrix} H_{ii} & 0 \\ 0 & I \end{bmatrix}
\]

Then, the estimation error has \( H_0 \) performance level \( \gamma_1 \) as expressed below,

\[
\lim_{t \to \infty} e(t) = 0, \quad \delta(t) = [(\dot{w}(t))^T, \dot{f}_s(t)]^T = 0
\]

With the following observer gain:

\[
K_n = \begin{bmatrix} K_n \quad 0 \end{bmatrix} = P^{-1} \bar{M}_i
\]

**III. Simulation tests**

In this section, fault estimation in a two tank hydraulic unit using the PIO and RO algorithms are examined. There are two interconnected tanks, two level sensors, two electric valves and a fluid supplying pump. The system state variables and control inputs are,

\[
x = [h_1, s_1, h_2, s_2]^T, \quad u = [v_1, v_2]^T
\]

Where \( h_i, s_i \) and \( v_i \) are the fluid level in a tank, valve opening and the valve controlling voltage of component \( i \).
The approximated TS fuzzy model of the fault infected system is given by \[ A_x = \begin{bmatrix} -1.29 & -3.125 & 0 & 0 \\ 0 & -0.377 & 0 & 0 \\ 1.29 & 3.125 & -1.29 & -3.125 \\ 0 & 0 & 0 & -0.377 \end{bmatrix}, \quad B_i = \begin{bmatrix} 0 & 0 \\ 13.3 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \]

\[
C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}
\]

\[
F_i = F_2 = 10^{-3} \begin{bmatrix} 0 & 0 & 5 \\ 0 & 1 & 1 \end{bmatrix}, \quad \quad H_i = 10^{-3} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \]

\[
F = \begin{bmatrix} 0 & 10 \end{bmatrix}, \quad x_0 = \begin{bmatrix} 0.25 \\ 0 \end{bmatrix}
\]

The results of the state estimation using the PIO and RO algorithms have been depicted in Fig. 2 and 3. As the figures indicate, both algorithms have successfully estimated the states despite of fault and noise. Distinctions between their outcomes are unnoticeable.

Table I illustrates amount of the obtained PI observer gains.

<table>
<thead>
<tr>
<th>( K )</th>
<th>( K_1 )</th>
<th>( K_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( K_{\mu} )</td>
<td>( 1.21 \times 10^7 )</td>
<td>( -137.64 )</td>
</tr>
<tr>
<td>( K_{\mu} )</td>
<td>( 6.16 \times 10^6 )</td>
<td>( 6.35 \times 10^6 )</td>
</tr>
<tr>
<td>( K_{\mu} )</td>
<td>( -142.38 )</td>
<td>( 6.35 \times 10^6 )</td>
</tr>
</tbody>
</table>

Table I. PI observer gains

<table>
<thead>
<tr>
<th>( \mu = 7.5132 )</th>
<th>( \lambda = 3.9647 \times 10^{11} )</th>
<th>( \lambda_0 = 3.6013 \times 10^{11} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( K_1 )</td>
<td>( 4.71 \times 10^7 )</td>
<td>( -2.05 \times 10^7 )</td>
</tr>
<tr>
<td>( K_2 )</td>
<td>( -1.26 \times 10^4 )</td>
<td>( 6.92 \times 10^4 )</td>
</tr>
<tr>
<td>( K_3 )</td>
<td>( 1.09 \times 10^4 )</td>
<td>( -4.49 \times 10^4 )</td>
</tr>
<tr>
<td>( K_4 )</td>
<td>( -2.12 \times 10^4 )</td>
<td>( 1.12 \times 10^4 )</td>
</tr>
</tbody>
</table>

Fig. 1. The two-tank hydraulic system [17].
Similarly, the algorithms give identical results concerning the sensor fault as it has been shown in Fig. 4. The fault consists of a step and a mounted sinusoidal disturbance, which may be infected by external interferences.

Fig. 5 gives information about error between sensor fault and fault estimation. Both algorithms RO and PIO perform as proper estimators, while the lower error has been obtained by RO algorithm in comparison to PIO algorithm.

However, the difference between the two algorithms emerges in the estimation of the actuator fault. Both algorithms with diverse quality detect the step like fault, which can be seen in Fig. 6. The PIO estimation is noisy, whereas RO delivers low variance estimation. From view of point of fault tracking speed, PIO looks more sensitive than RO, particularly at the moment of occurring fault. As less variance is a more important quality factor for any estimation algorithms, one will prefer RO to PIO in the procedure of an actuator fault detection. In addition to, Fig. 7 gives more information about the resulting error between actuator fault and its estimation.

IV. CONCLUSION

In this work, estimation of sensor and actuator fault in a two-tank system are investigated by using the PIO and RO algorithms. Despite of the existence of the process noise, both algorithms would be able to the accurate estimation of the states and sensor faults. However, the quality of outcome differs in estimating the actuator fault. RO returns a smoother estimates of fault whiles PIO outcome is noisy. On the other hand, the fault tracking speed of PIO advances RO. In general, RO looks more appropriate for using as an actuator fault estimator in a noisy environment than more agile PIO.

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