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On-line Parameter Estimator Based on Takagi-Sugeno Fuzzy Models

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Abstract

In this paper, a new on-line parameter estimation methodology for the general continuous time Takagi-Sugeno(T-S) fuzzy model whose parameters are poorly known or uncertain is presented. An estimator with an appropriate adaptive law for updating the parameters is designed and analyzed based on the Lyapunov theory. The adaptive law is designed so that the estimation model follows the plant parameterized model. By the proposed estimator, the parameters of the T-S fuzzy model can be estimated by observing the behavior of the system and it can be a basis for the indirect adaptive fuzzy control. Based on the derived design method, the parameter estimation for controllable canonical T-S fuzzy model is also presented.

Key Words : Parameter estimation, Takagi-Sugeno fuzzy model, fuzzy systems, adaptive control, nonlinear system.

Ⅰ. Introduction

Fuzzy controllers are assumed to work in the situations where the plant parameters and structures have some uncertainties or unknown variations. The objective of adaptive control is to maintain the consistent performance of a system in the presence of the uncertainties. So advanced fuzzy control might be adaptive. An adaptive fuzzy system is a fuzzy logic system equipped with an adaptive law. The major advantage of the adaptive fuzzy controller over the conventional adaptive controller is that the adaptive fuzzy controller is capable of incorporating linguistic information from human operators[1].

The adaptive fuzzy controllers are divided into two classes. One is called the direct adaptive fuzzy control and the other is called the indirect adaptive fuzzy control. In the direct adaptive fuzzy control, we view the fuzzy logic systems as controllers. However, in the indirect adaptive fuzzy control, the fuzzy logic systems are used to model the plant. Then the controller is constructed assuming that the fuzzy logic systems approximately represent the true plant and an appropriate adaptive law plays an important role in estimating the parameters in the fuzzy model representing the plant model, whose parameters are unknown or varying due to the external disturbances and parameter perturbation. Hence, the parameter estimation for the fuzzy model is essential to the indirect adaptive fuzzy control.

Hitherto, some studies on the parameter estimation of the fuzzy system from the input-output measurements have been conducted. The estimation algorithm of fuzzy relational model in [2]. The parameter estimation of Takagi-Sugeno (T-S) fuzzy system have been derived in [3-5]. A qualitative modeling of a fuzzy system was presented in [6] and neural-network-based approaches have been made in [7] and [8].

However, most of these are the off-line algorithm and cannot be applied to the situations where a real-time processing is required such as adaptive control and signal processing. Even though the successive adaptive fuzzy modeling was suggested in [9], it cannot be viewed as an on-line algorithm in an actual sense since it requires off-line learning phase before being adapted on-line. Furthermore, many on-line parameter estimation schemes used in the indirect adaptive fuzzy control[10-15] can be only applied to the specified fuzzy controller, mainly feedback linearization based controllers. Hence the parameter estimation scheme applicable to the general fuzzy model and controllers is needed.

To avoid these problems, this paper presents a new design and an analysis of the on-line parameter estimator for the plant model whose structure is represented by the general T-S fuzzy model without considering any specific controllers. The essential idea behind the on-line estimation is the comparison of the measured state $x(t)$ with $\hat{x}(t)$ of a estimation model whose structure is the same as that of the parameterized plant model. The parameters are adjusted continuously so that $\hat{x}(t)$ approaches $x(t)$ as time increases.

Ⅱ. Takagi-Sugeno Fuzzy Model

As an expression model of a real plant we use the fuzzy implications and the fuzzy reasoning methods

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suggested by Takagi and Sugeno[3]. The set of fuzzy implications shown in the Takagi and Sugeno(T-S) model can express a highly nonlinear functional relation in spite of a small number of fuzzy implication rule. As a describing rule the T-S fuzzy model uses fuzzy implication of the following form:

$$R^i: \ \textit{If } x_1(t) \textit{ is } M_1^i \text{ and } \cdots \text{ and } x_n(t) \textit{ is } M_n^i \quad \textit{then } \ \dot{\boldsymbol{x}}(t) = A_i\boldsymbol{x}(t) + B_i\boldsymbol{u}(t) \tag{1}$$

where $R^i(i=1,2,\cdots,l)$ denotes the ith implication, l is the number of fuzzy implications, M_j^i are fuzzy sets and $\boldsymbol{x}^T(t) = [x_1(t), x_2(t), \cdots, x_n(t)]$,

$\boldsymbol{u}^T(t) = [u_1(t), u_2(t), \cdots, u_m(t)]$.

The T-S fuzzy model approximates a nonlinear system with a combination of several linear systems. The overall T-S fuzzy model is formed by fuzzy partitioning of the input space. The premise of a fuzzy implication indicates a fuzzy subspace of the input space and each consequent expresses a local input-output relation in the subspace corresponding to the premise part.

Given a pair of input $(\boldsymbol{x}(t), \boldsymbol{u}(t))$, the final output of the fuzzy system is inferred as follows:

$$\dot{\boldsymbol{x}}(t) = \frac{\sum_{i=1}^{l} w_i(\boldsymbol{x}(t))\{A_i\boldsymbol{x}(t)+B_i\boldsymbol{u}(t)\}}{\sum_{i=1}^{l} w_i(\boldsymbol{x}(t))} \tag{2}$$

where $w_i(\boldsymbol{x}(t)) = \prod_{j=1}^{n} M_j^i(x_j(t))$, $M_j^i(x_j(t))$ is the grade of membership of $x_j(t)$ in M_j^i and it is assumed that $\sum_{i=1}^{l} w_i(\boldsymbol{x}(t)) > 0$, $w_i(\boldsymbol{x}(t)) \geq 0$, for $i=1,2,\cdots,l$.

III On-line parameter estimation for general T-S fuzzy model

To develop the parameter estimator for the T-S fuzzy modeled plant, we start with the plant parameterization as

$$\begin{aligned}\dot{\boldsymbol{x}} &= \frac{\sum_{i=1}^{n} w_i(A_i\boldsymbol{x}+B_i\boldsymbol{u}+A_m\boldsymbol{x}-A_m\boldsymbol{x})}{\sum_{i=1}^{n} w_i} \\ &= A_m\boldsymbol{x} + \frac{\sum_{i=1}^{n} w_i((A_i-A_m)\boldsymbol{x}+B_i\boldsymbol{u})}{\sum_{i=1}^{n} w_i}\end{aligned} \tag{3}$$

where A_m is a stable matrix, i.e., has all its eigenvalues in the left half plane.

Now, we define the estimation model as

$$\dot{\hat{\boldsymbol{x}}} = A_m\hat{\boldsymbol{x}} + \frac{\sum_{i=1}^{n} w_i((\widehat{A}_i-A_m)\boldsymbol{x}+\widehat{B}_i\boldsymbol{u})}{\sum_{i=1}^{n} w_i}, \tag{4}$$

where $\widehat{A}_i(t)$, $\widehat{B}_i(t)$ are the estimates of A_i, B_i at time t to be generated by an adaptive law, and $\hat{\boldsymbol{x}}(t) \in R^n$ is the estimate of the vector $\boldsymbol{x}(t)$.

Remark 1: In this paper, to derive the adaptive law, we use series-parallel estimation model configuration, which has been widely used for a parameter estimation model for considering the parameterization of the plant model[17]. Different from another parameterization method, parallel model configuration in which only $\hat{x}$ is used, the estimate $\hat{x}$ for x is generated using the real state x and the forced control input u in the series-parallel model configuration.

By defining the estimation error vector $\boldsymbol{\varepsilon}_1$ as

$$\boldsymbol{\varepsilon}_1 \triangleq \boldsymbol{x} - \hat{\boldsymbol{x}}$$

we obtain

$$\begin{aligned}\dot{\boldsymbol{\varepsilon}}_1 &= \dot{\boldsymbol{x}} - \dot{\hat{\boldsymbol{x}}} \\ &= A_m\boldsymbol{\varepsilon}_1 - \frac{\sum w_i\widetilde{A}_i}{\sum w_i}\boldsymbol{x} - \frac{\sum w_i\widetilde{B}_i}{\sum w_i}\boldsymbol{u}\end{aligned} \tag{5}$$

where $\widetilde{A}_i \triangleq \widehat{A}_i - A_i$, $\widetilde{B}_i \triangleq \widehat{B}_i - B_i$

Let us now consider the series-parallel model design and use (5) to derive the adaptive law for estimating the elements of A_i, B_i. We assume that the adaptive law has the general structure

$$\dot{\widehat{A}}_i = F_i(\boldsymbol{x}, \hat{\boldsymbol{x}}, \boldsymbol{\varepsilon}_1, \boldsymbol{u}), \ \dot{\widehat{B}}_i = G_i(\boldsymbol{x}, \hat{\boldsymbol{x}}, \boldsymbol{\varepsilon}_1, \boldsymbol{u}) \tag{6}$$

where F_i and G_i $(i=1,\cdots,l)$ are functions of known signals that are to be chosen so that the equilibrium

$$\widehat{A}_{ie} = A_i, \ \widehat{B}_{ie} = B_i, \ \boldsymbol{\varepsilon}_{1e} = 0 \tag{7}$$

of (5), (6) has some desired stability properties. By choosing the following function as the Lyapunov function candidate,

$$\begin{aligned}V(\boldsymbol{\varepsilon}_1, \widetilde{A}_i, \widetilde{B}_i) = \ &\boldsymbol{\varepsilon}_1^T P\boldsymbol{\varepsilon}_1 + \sum_{i=1}^{l} tr\left(\frac{\widetilde{A}_i^T P\widetilde{A}_i}{\gamma_{1i}}\right) \\ &+ \sum_{i=1}^{l} tr\left(\frac{\widetilde{B}_i^T P\widetilde{B}_i}{\gamma_{2i}}\right)\end{aligned} \tag{8}$$

where $tr(A)$ denotes the trace of a matrix A, γ_{1i}, $\gamma_{2i} > 0$ are constant scalars, and $P = P^T > 0$ is chosen as the solution of the Lyapunov equation

$$A_m^T P + PA_m = -I \tag{9}$$

whose existence is guaranteed by the stability assumption of A_m, we obtain the time derivative $\dot{V}$ of

V along the trajectory of (5), (6), which is given by

$$\dot V = -\epsilon_1^T\epsilon_1 - 2\epsilon_1^T P\frac{\sum w_i\tilde A_i}{\sum w_i}x - 2\epsilon_1^T P\frac{\sum w_i\tilde B_i}{\sum w_i}u + \sum 2tr\left(\frac{\tilde A_i^T PF_i}{\gamma_{1i}}\right) + \sum 2tr\left(\frac{\tilde B_i^T PG_i}{\gamma_{2i}}\right) \tag{10}$$

After some straightforward manipulation on (10), we have

$$\begin{aligned}\dot V = & -\epsilon_1^T\epsilon_1 \\ & + 2tr\left(\sum\frac{\tilde A_i^T PF_i}{\gamma_{1i}} - \frac{\sum w_i\tilde A_i^T}{\sum w_i}P\epsilon_1 x^T\right. \\ & \left. + \sum\frac{\tilde B_i^T PG_i}{\gamma_{2i}} - \frac{\sum w_i\tilde B_i^T}{\sum w_i}P\epsilon_1 u^T\right)\end{aligned} \tag{11}$$

The obvious choice for F_i, G_i to make $\dot V$ negative is

$$\sum\frac{\tilde A_i^T PF_i}{\gamma_{1i}} = \frac{\sum w_i\tilde A_i^T}{\sum w_i}P\epsilon_1 x^T,$$

$$\sum\frac{\tilde B_i^T PG_i}{\gamma_{2i}} = \frac{\sum w_i\tilde B_i^T}{\sum w_i}P\epsilon_1 u^T$$

That is,

$$\dot{\hat A}_i = F_i = \gamma_{1i}\frac{w_i}{\sum w_i}\epsilon_1 x^T \tag{12a}$$

$$\dot{\hat B}_i = G_i = \gamma_{2i}\frac{w_i}{\sum w_i}\epsilon_1 u^T \tag{12b}$$

The signals for driving the adaptation law (12a) and (12b) of the parameter estimator are known or available for measurement. Therefore, the estimation law for the estimation model (4) can be implemented. The overall estimation scheme is shown in Fig. 1.

We establish the following theorem, which shows the properties of the adaptive law (12).

Theorem 1: Consider the plant model (2) and the estimation model (4) with the estimation law (12). Assume $u \in \mathcal{L}_\infty$. and then, the adaptive law (12) guarantees that

(i) $|\epsilon_1(t)| \to 0$ as $t \to \infty$

(ii) $\|\tilde A_i(t)\| \to 0$, $\|\tilde B_i(t)\| \to 0$ as $t \to \infty$

Proof: From the adaptive law (12), it directly follows that the time derivative $\dot V$ of V along the solution trajectory of (5), (6) satisfies

$$\dot V = -\epsilon_1^T\epsilon_1 \le 0 \tag{13}$$

Since the function V is a Lyapunov function for the system (5), (6) where x and u are treated as independent bounded functions of time, and $\dot V \le 0$, we conclude that the equilibrium given by (7) is uniformly stable, which implies that the trajectory $\epsilon_1(t)$, $\tilde A_i(t)$, $\tilde B_i(t)$ is bounded for all $t > 0$.

Because $\epsilon_1 = x - \hat x$ and $x \in \mathcal{L}_\infty$, we also have that $\hat x \in \mathcal{L}_\infty$. Therefore, all signals in (5) and (6) are uniformly bounded.

From (8) and (13), we conclude that because V is bounded from below and it has a limit, i.e.,

$$\lim_{t\to\infty} V(\epsilon_1(t), \tilde A_i(t), \tilde B_i(t)) = V_\infty < \infty \tag{14}$$

From (13) and (14), it follows that

$$\int_0^\infty \epsilon_1^T\epsilon_1 d\tau = -\int_0^\infty \dot V d\tau = (V_0 - V_\infty) \tag{15}$$

where

$$V_0 = V(\epsilon_1(0), \tilde A_i(0), \tilde B_i(0))$$

which implies that $\epsilon_1 \in \mathcal{L}_2$. Because $0 \le w_i(x) \le 1$, and $u, \tilde A_i, \tilde B_i, \hat x, \epsilon_1 \in \mathcal{L}_\infty$, it follows from (5) that $\dot\epsilon_1 \in \mathcal{L}_\infty$, which, together with $\epsilon_1 \in \mathcal{L}_2$, implies that $\epsilon_1 \to 0$ as $t \to \infty$, which, in turn, implies that $\tilde A_i(t), \tilde B_i(t) \to 0$ as $t \to \infty$.

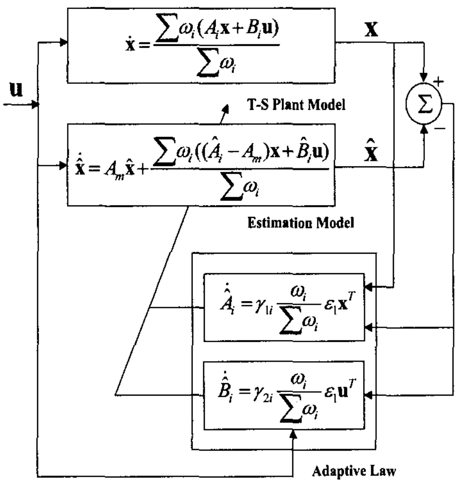

Fig. 1 T-S fuzzy model parameter estimator

Ⅳ. Parameter Estimation for controllable canonical T-S fuzzy model

In the previous section, we have presented an on-line parameter estimation for the SISO general T-S fuzzy model. Based on the analysis, in this section, we consider the following T-S fuzzy model whose consequent parts have a controllable canonical form representation and the estimator for the parameters comprising the canonical T-S fuzzy model which has been widely used in the practical modeling problems is designed.

$$\dot{\boldsymbol{x}} = \frac{\sum_{i=1}^{L} w_i(\boldsymbol{x})\left\{\begin{bmatrix} a_n^i & a_{n-1}^i & \cdots & a_2^i & a_1^i \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}\boldsymbol{x} + \begin{bmatrix} b_i \\ 0 \\ \vdots \\ 0 \end{bmatrix} u\right\}}{\sum_{i=1}^{L} w_i(\boldsymbol{x})} \tag{16}$$

where state $\boldsymbol{x}^T = [x_n, x_{n-1}, \cdots, x_1]$ and input $u \in R^1$ are available for measurement, $\boldsymbol{a}_i^T = [a_n^i, a_{n-1}^i, \cdots, a_1^i]$, $b^i \in R^1$ $(i=1,\cdots,l)$ are unknown, and $u \in \mathcal{L}_\infty$, $w_i(\boldsymbol{x}) = \prod_{j=1}^{p} M_j^i(\boldsymbol{x})$.

By considering the plant parameterization

$$\dot{\boldsymbol{x}} = A_m \boldsymbol{x} + \frac{\sum_{i=1}^{L} w_i(\boldsymbol{x})((A_i - A_m)\boldsymbol{x} + B_i u)}{\sum_{i=1}^{L} w_i(\boldsymbol{x})}$$

where $A_i = \begin{bmatrix} a_n^i & a_{n-1}^i & \cdots & a_2^i & a_1^i \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}$, $B_i = \begin{bmatrix} b_i \\ 0 \\ \vdots \\ 0 \end{bmatrix}$ and A_m is a stable matrix of the same form as A_i, we define the estimation model as

$$\hat{\boldsymbol{x}} = A_m \hat{\boldsymbol{x}} + \frac{\sum_{i=1}^{L} w_i(\boldsymbol{x})((\widehat{A}_i(t) - A_m)\boldsymbol{x} + \widehat{B}_i(t)\, u)}{\sum_{i=1}^{L} w_i(\boldsymbol{x})} \tag{17}$$

The estimation error vector $\boldsymbol{\varepsilon}_1$ defined $\boldsymbol{\varepsilon}_1 \triangleq \boldsymbol{x} - \hat{\boldsymbol{x}}$ satisfies

$$\begin{aligned} \dot{\boldsymbol{\varepsilon}}_1 &= \dot{\boldsymbol{x}} - \dot{\hat{\boldsymbol{x}}} \\ &= A_m \boldsymbol{\varepsilon}_1 + \frac{\sum w_i \left\{ -\begin{bmatrix} \tilde{\boldsymbol{a}}_i^T \\ 0 \\ \vdots \\ 0 \end{bmatrix} \boldsymbol{x} - \begin{bmatrix} \tilde{b}_i \\ 0 \\ \vdots \\ 0 \end{bmatrix} u \right\}}{\sum w_i} \\ &= A_m \boldsymbol{\varepsilon}_1 - \frac{\sum w_i [\, \tilde{\boldsymbol{a}}_i \; 0 \cdots 0]^T}{\sum w_i} \boldsymbol{x} \\ &\quad - \frac{\sum w_i [\, \tilde{b}_i \; 0 \cdots 0]^T}{\sum w_i} u \end{aligned} \tag{18}$$

where $\tilde{\boldsymbol{a}}_i^T \triangleq \hat{\boldsymbol{a}}_i^T - \boldsymbol{a}_i^T$, $\tilde{b}_i \triangleq \hat{b}_i - b_i$

Now by using the estimation error dynamics (18), we derive the adaptive law for updating the elements of $\boldsymbol{a}_i^T$, b_i so that the estimation model (17) having updated parameters follows the plant model (16). We assume that the adaptive law has the general structure

$$\dot{\hat{\boldsymbol{a}}}_i^T = f_i^T(\boldsymbol{x}, \hat{\boldsymbol{x}}, \boldsymbol{\varepsilon}_1, u) \tag{19}$$

$$\dot{\hat{b}}_i = g_i(\boldsymbol{x}, \hat{\boldsymbol{x}}, \boldsymbol{\varepsilon}_1, u) \tag{20}$$

where f_i^T and g_i $(i=1,\cdots,l)$ are functions of known signals.

Let us choose the following function as a Lyapunov function candidate

$$V(\boldsymbol{\varepsilon}_1, \tilde{\boldsymbol{a}}_i, \tilde{b}_i) = \boldsymbol{\varepsilon}_1^T P \boldsymbol{\varepsilon}_1 + \sum_{i=1}^{L} \frac{\tilde{\boldsymbol{a}}_i^T \tilde{\boldsymbol{a}}_i}{\gamma_{1i}} + \sum_{i=1}^{L} \frac{\tilde{b}_i^2}{\gamma_{2i}} \tag{21}$$

where $\gamma_{1i}, \gamma_{2i} > 0$ are constants, and $P = P^T > 0$ is chosen as the solution of the Lyapunov equation

$$A_m^T P + P A_m = -I \tag{22}$$

The time derivative $\dot{V}$ of V along the trajectory of (18), (19) is given by

$$\begin{aligned} \dot{V} = &- \boldsymbol{\varepsilon}_1^T \boldsymbol{\varepsilon}_1 - 2\frac{\sum w_i \; \boldsymbol{p}_1^T \boldsymbol{\varepsilon}_1 \boldsymbol{x}^T \tilde{\boldsymbol{a}}_i}{\sum w_i} \\ &- 2\frac{\sum w_i \tilde{b}_i}{\sum w_i} \boldsymbol{p}_1^T \boldsymbol{\varepsilon}_1 u \\ &+ \sum_{i=1}^{N} 2\frac{\dot{\tilde{\boldsymbol{a}}}_i^T \tilde{\boldsymbol{a}}_i}{\gamma_{1i}} + \sum_{i=1}^{N} 2\frac{\tilde{b}_i \dot{\tilde{b}}_i}{\gamma_{2i}} \end{aligned} \tag{23}$$

Since the primary objective of the adaptive law is to stabilize the estimation error dynamics we have to choose the adaptive law such that it makes $\dot{V}$ to be negative. The obvious choice to make $\dot{V}$ negative is

$$\dot{\tilde{\boldsymbol{a}}}_i^T = \dot{\hat{\boldsymbol{a}}}_i^T = f_i^T = \gamma_{1i}\frac{w_i}{\sum w_i} \boldsymbol{p}_1^T \boldsymbol{\varepsilon}_1 \boldsymbol{x}^T \tag{24a}$$

$$\dot{\tilde{b}}_i = \dot{\hat{b}}_i = g_i = \gamma_{2i}\frac{w_i}{\sum w_i} \boldsymbol{p}_1^T \boldsymbol{\varepsilon}_1 u \tag{24b}$$

Now, let us consider the properties of the adaptive law (24), which are given in the following theorem.

Theorem 2: Consider the plant model (16) and the estimation model (17) with the estimation law (24). Assume that $u \in \mathcal{L}_\infty$, and then, the adaptive law (24) guarantees that

(i) $|\boldsymbol{\varepsilon}_1(t)| \to 0$ as $t \to \infty$

(ii) $\|\hat{\boldsymbol{a}}_i(t)\| \to 0$, $\|\hat{b}_i(t)\| \to 0$ as $t \to \infty$

Proof: Since the estimation for the controllable canonical form T-S fuzzy model is a special case of the general T-S fuzzy model estimation given in the previous section, by following the procedure similar to that of the proof of Theorem 1, we can easily prove the above theorem.

V. Conclusion

The on-line parameter estimation scheme for the general T-S fuzzy model has been designed and analyzed. The adaptive law adjusting the parameters has been formulated based on the Lyapunov theory so that the parameter estimation was guaranteed. Hence, it can be used in the case where the plant parameters in the T-S fuzzy model are uncertain. We have also presented the estimator for the parameters comprising the controllable canonical T-S fuzzy model by following the proposed design method. Combining the proposed on-line estimation scheme with any other T-S fuzzy model based state feedback controller can give a good robust performance to the T-S fuzzy control systems in the sense of an indirect adaptive control methodology.

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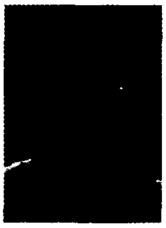

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