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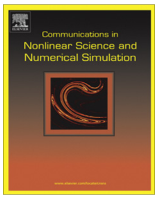

Short communication

State estimation with guaranteed performance for switching-type fuzzy neural networks in presence of sensor nonlinearities

Yanghui Xu [1], Dan Zhang *

Department of Automation, Zhejiang University of Technology, Hangzhou 310032, PR China

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ABSTRACT

This paper investigates the state estimation with guaranteed performance for a class of switching fuzzy neural networks. A switching-type fuzzy neural networks (STFNNs) model is proposed which captures external disturbances, sensor nonlinearities, and mode switching phenomenon of the fuzzy neural networks without the Markovian process assumption. For such a model, a state estimation problem is formulated to achieve the guaranteed performance: the estimation error system is exponentially stable with certain decay rate and a prescribed H_∞ disturbance attenuation level. A novel sufficient condition for this problem is established using the Lyapunov functional method and the average dwell time approach, and the estimator parameters are explicitly given. A numerical example is presented to show the effectiveness of the developed results.

1. Introduction

In recent years, neural networks (NNs) have received considerable attention since they have found extensive application in various areas such as signal processing, pattern recognition, static image processing, associative memory and combinatorial optimization. In practice, due to the finite speed of information processing, time delay is frequently encountered in NNs, which may cause oscillation and instability of NNs [1]. Therefore, considerable efforts have been devoted on the stability analysis of delayed neural networks (DNNs) in the past decade, see [2–10].

It is known that the Markovian jumping systems (MJSs) are a special class of hybrid systems, which is specified by two components in the state. The first one is the mode, which is described by a continuous-time finite-state Markovian process, and the second one refers to the state which is represented by a system of differential equations. The MJSs have the advantage of modeling the dynamic systems subject to abrupt variation in their structures, such as component failures and sudden environmental disturbance. In recent years, the MJS approach has been introduced to model the mode/parameter switching of the neural networks. For example, the stochastic exponential stability was investigated in [11] for the Markovian jumping bidirectional associative memory (BAM) neural networks with time-varying delays. In [12] and [13], the problem of delay-dependent stochastic stability for the Hopfield neural networks with Markovian jumping parameters and time delay was considered.

In many practical systems, however, the occurrence of component failures and sudden environmental disturbance may not always obey the Markov process. In this case, the switched hybrid system (SHS) approach provides an effective way to model these phenomena. For example, the switched system approach was used to model the controller failure in control

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* Corresponding author. Tel.: +86 571 85290601.
E-mail address: jason_zhang19850626@hotmail.com (D. Zhang).

[1] Address: Health Management Service Center & International Liaison Office, Zhejiang Hospital, Hangzhou 310013, PR China.

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systems [14], and the switched system approach was used to model the link failure in the synchronization of complex networks [15]. The difference between the MJSs and the SHSs is that the switching of the SHSs is arbitrary rather than obeying the Markov process, thus, it is more applicable in the modeling of practical systems. Up to now, many approaches have been developed to study the SHSs, e.g. multiple Lyapunov functional approach, switched Lyapunov functional approach, average dwell time approach. More recently, increasing research attention has been paid to stability analysis of neural networks with switching-type parameters, and recent advancement can be found in [16–19].

The well known Takagi–Sugeno (T–S) fuzzy model [20] is recognized as an efficient tool in approximating a complex nonlinear system. The T–S fuzzy model approach is essentially a multi-model approach which is locally a linear time-invariant system connected by IF–THEN rules. During the last decades, considerable research attention has been focused on the stability analysis and control synthesis of T–S fuzzy systems with or without time delays, see [21–26] and the references therein. Recently, the T–S fuzzy model approach has been used to investigate nonlinear MJSs [27–29]. A sufficient condition for designing H_∞ filter for fuzzy MJSs was obtained in [27]. In [30], the authors firstly introduced the fuzzy Hopfield neural networks with Markovian jumping parameters, and the robust asymptotic stability condition was obtained. More recently in [31], the global asymptotic stability analysis of fuzzy Markovian jumping Cohen–Grossberg BAM neural networks with mixed time-varying delays was studied. Although some stability results have been derived for the delayed fuzzy neural networks with Markovian parameter switching, as we mentioned before, the more practical case is that the parameter is switching arbitrarily. So, the first natural question is asked: if the parameter switching is governed by an arbitrary switching rule, but not the specified Markovian process, how can we *analyze the fuzzy neural networks with the switching-type parameters*? However, to the best of the author's knowledge, such an interesting problem has not received enough attention, and it still remains challenging and open.

On the other hand, in relatively large-scale neural networks, it is often that only partial information about the neuron states is available in the network outputs, in this case, the neuron state estimation problem becomes important for the applications that need to utilize the estimated neuron state. In [32], the authors firstly investigated the state estimation problem for continuous-time neural networks with time-varying delay through available output measurements and derived some procedures to design estimator gain. Since then, the state estimation problem has been further investigated for various neural networks, see, e.g. [33–45]. It is seen that in above state estimation results, the measurement output is always described by $y(t) = Cx(t) + f(x(t))$, where $Cx(t)$ is the sensor's *ideal* measurement and $f(x(t))$ is the nonlinear disturbance on the network outputs. However, in many industrial applications, measurements are often made under harsh environments that include both uncontrollable elements (e.g. variations in flow rates and temperatures) and aggressive conditions (e.g. corrosion, and fouling) [46]. In these cases, cheap sensors must be used since sensors need to be replaced very often. However, the range limitations will result in the *nonlinear characteristics* of cheap sensors. Thus, the sensor's *ideal* measurement $Cx(t)$ is a *nonlinear term*, which exhibits the *completely nonlinear* measurement output. Due to its practical importance, the sensor nonlinearity problem has recently been studied in the control community [47,48]. However, little attention has been paid on the design of state estimator for neural networks. The second natural question we face now is can we estimate the neuron states with the existence of *sensor's nonlinear characteristics*?

Motivated by the above discussion, we investigate the state estimation for the switching-type fuzzy neural networks (STFNNs) with time-varying delay and sensor nonlinearities to answer the two questions above. The STFNNs model is proposed to describe the general mode switching of the fuzzy neural networks, and the state estimation is then studied for the STFNNs with two guaranteed performance indices. Specifically, the objective of this paper is to design a state estimator such that for the existence of sensor's nonlinearities and the external disturbance, the estimation error system is exponentially stable with certain decay rate, and a prescribed H_∞ disturbance attenuation level is also guaranteed. By using the average dwell time approach and the piecewise Lyapunov functional technique, a novel sufficient condition is proposed to solve the considered problem. The estimator gains can be explicitly obtained by solving some linear matrix inequalities (LMIs). A numerical example is finally given to show the effectiveness of the developed results.

2. Problem formulation

Let us first revisit the model of Markovian jumping fuzzy neural networks (MJFNNs) in [30]. For each mode $\sigma(t)$, the ith rule of this T–S fuzzy model is as follows:

Plant Rule i: IF $\theta_1(t)$ is ϑ_{1i} and $\theta_2(t)$ is ϑ_{2i},..., and $\theta_\upsilon(t)$ is $\vartheta_{\upsilon i}$, Then

$$\dot{x}(t) = -A_i(\sigma(t))x(t) + C_i(\sigma(t))g(x(t-d(t))), \tag{1}$$

where $\theta_1(t), \theta_2(t), \ldots, \theta_\upsilon(t)$ are the premise variables, $\vartheta_{1i}, \vartheta_{2i}, \ldots, \vartheta_{\upsilon i}$ are the fuzzy sets $x(t) = [x_1(t), x_2(t), \ldots, x_n(t)]^T \in \mathrm{R}^n$ is the neuron state, and $g(x(\bullet)) = [g_1(x_1(\bullet)), g_2(x_2(\bullet)), \ldots, g_n(x_n(\bullet))]^T \in \mathrm{R}^n$ is the nonlinear activation function, which satisfies

$$|g_q(\xi_1) - g_q(\xi_2)| \leqslant \omega_q|\xi_1 - \xi_2|, \xi_1, \xi_2 \in \mathrm{R},\ \xi_1 \neq \xi_2;\ q = 1, 2, \ldots, n. \tag{2}$$

$A_i(\sigma(t)) = diag\{a_1^i(\sigma(t)), a_2^i(\sigma(t)), \ldots, a_n^i(\sigma(t))\}$,, $C_i(\sigma(t)) = (c_{pq}^i(\sigma(t)))_{n\times n}$ are the constant matrices with appropriate dimensions. $d(t)$ is the time-varying delay, and is assumed to satisfy $d_1 \leqslant d(t) \leqslant d_2$. $\{\sigma(t), t \geqslant 0\}$ is a homogeneous finite-state Markovian process with right continuous trajectories and taking values in finite set $S = \{1, 2, \ldots, s\}$ with the initial model σ_0.

Then, for each mode $\sigma(t) = l$, the defuzzified output of system (1) is referred as follows: