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Receding horizon disturbance attenuation for Takagi–Sugeno fuzzy switched dynamic neural networks

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ABSTRACT

In this paper, we propose a new receding horizon disturbance attenuator (RHDA) for Takagi–Sugeno (T–S) fuzzy switched Hopfield neural networks with external disturbance. First, a new set of linear matrix inequality (LMI) conditions is proposed for the finite terminal weighting matrix of the receding horizon cost function with a cross term. Second, under this condition, we show that the proposed RHDA attenuates the effect of external disturbance on T–S fuzzy switched Hopfield neural networks with a guaranteed infinite horizon $\mathcal{H}_\infty$ performance. In addition, we prove that the proposed RHDA guarantees internal stability in closed-loop systems. A numerical example is presented to describe the effectiveness of the proposed RHDA scheme.

1. Introduction

Hopfield neural networks [23] have been extensively investigated in recent years because of their widespread use in modeling many phenomena associated with signal processing, pattern recognition, associative memory, static image processing, and particularly in solving difficult optimization problems [21]. Therefore, the various stability properties (e.g., asymptotic, exponential, and stochastic stability) need to be studied for different types of Hopfield neural networks.

Switched systems form an important class of hybrid systems consisting of a finite number of subsystems described by dynamic systems and a switching signal that specifies the switching among them. Switched systems are formed when dynamic systems undergo abrupt changes due to parameter changes, component failures, or element switching. Experiments using various techniques have shown many important and interesting results for switched systems, owing to their theoretical and practical significance [20,44,45,31]. Recently, the use of switched Hopfield neural networks, whose subsystems constitute a set of Hopfield neural networks, has been widely applied in the field of high-speed signal processing and in gene selection in DNA microarray analyses [37,19,30]. Some stability conditions for switched Hopfield neural networks were investigated in [25,27,1]. New results on learning, filtering, and estimation in switched Hopfield neural networks were presented in [3,4,9,7,10].

Recently, the Takagi–Sugeno (T–S) fuzzy model approach was used to describe neural networks and the problem of stability analysis for T–S fuzzy Hopfield neural networks was extensively studied in [24,17,26]. Among the different types of fuzzy methods, the T–S fuzzy models [35,36] have attracted particular attention from researchers because these models can effectively approximate a wide class of complex nonlinear systems by using some local linear subsystems. The T–S fuzzy

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model approach is a multi-model approach in which some linear models are combined to form an overall single model through nonlinear membership functions to represent nonlinear system dynamics. The nonlinear system dynamics are captured by a set of fuzzy rules that characterize local correlation in the state space. Some new results on learning, identification, filtering, and stabilization in T–S fuzzy Hopfield neural networks were presented in [2,5,6,8,11,14].

The receding horizon approach is now accepted as an important feedback strategy in many industry fields, especially in process industries [38,39,28,22,40,14]. This approach has many advantages, such as guaranteed robustness and adaptation to switched parameters. Since control methods based on the receding horizon approach are computed repeatedly under a cost function, the approach can adapt to unanticipated changes in system parameters. In [29], the receding horizon approach was applied to the nonlinear $\mathcal{H}_\infty$ control problem. However, the inverse optimality based result was obtained simply via a Fake Hamilton–Jacobi–Isaacs equation. Recently, the receding horizon $\mathcal{H}_\infty$ approach was proposed to solve chaos synchronization and nonlinear neural control problems in [12,13], respectively. To the best of our knowledge, the problem of receding horizon disturbance attenuation for T–S fuzzy switched Hopfield neural networks with external disturbance has not been investigated thus far and remains an open and challenging research topic.

In this paper, we propose a new receding horizon disturbance attenuator (RHDA) for T–S fuzzy switched Hopfield neural networks with external disturbance. A new set of sufficient linear matrix inequality (LMI) conditions is proposed for the finite terminal weighting matrix of the receding horizon cost function with a cross term, under which the proposed RHDA reduces the effect of external disturbance in T–S fuzzy switched Hopfield neural networks. The proposed RHDA guarantees asymptotic stability in T–S fuzzy switched Hopfield neural networks without external disturbance. The finite terminal weighting matrix in the receding horizon cost function can be determined by solving a set of LMI conditions. This LMI problem can be solved efficiently by using standard convex optimization software [18].

This paper is organized as follows. In Section 2, we formulate the problem. In Section 3, a new set of sufficient LMI conditions is proposed for the receding horizon disturbance attenuation of T–S fuzzy switched Hopfield neural networks with external disturbance. In Section 4, a numerical example is given, and finally, conclusions are presented in Section 5.

2. Problem formulation

Consider the following T–S fuzzy switched Hopfield neural network:

Fuzzy Rule $\mathbb{R}^i_\alpha$:

IF ω_1 is $\mu^i_{\alpha 1}$ and $\cdots \omega_s$ is $\mu^i_{\alpha s}$ **THEN**

$$\dot{x}(t) = A(i,\alpha)x(t) + W(i,\alpha)\phi(x(t)) + u(t) + w(t), \tag{1}$$

where ω_j $(j = 1,2,\ldots,s)$ is the premise variable, $\mu^i_{\alpha j}$ $(i = 1,2,\ldots,r, j = 1,2,\ldots,s)$ is the fuzzy set that is characterized by a membership function, r is the number of IF-THEN rules, s is the number of premise variables, $x(t) = [x_1(t), x_2(t),\ldots,x_n(t)]^T \in R^n$ is the state vector, $A(i,\alpha) \in R^{n\times n}$ is the negative diagonal matrix representing the self-feedback term, $W(i,\alpha) \in R^{n\times n}$ is the connection weight matrix, $\phi(x(t)) = [\phi_1(x(t)), \phi_2(x(t)),\ldots,\phi_n(x(t))]^T : R^n \to R^n$ is the nonlinear function vector satisfying the global Lipschitz condition with Lipschitz constant $L_\phi > 0, u(t) \in R^n$ is the control input vector, and $w(t) \in R^n$ is the external disturbance vector. Here, α is a switching signal that can have any value from the finite set $\{1,2,\ldots,N\}$. The matrices $(A(i,\alpha), W(i,\alpha))$ are allowed to take values in the finite set $\{(A(i,1), W(i,1)),\ldots,(A(i,N), W(i,N))\}$ at an arbitrary time for $i = 1,2,\ldots,r$. This study assumes that the switching rule α is not known a priori and its instantaneous value is available in real time. A standard fuzzy inference method is used, and system (1) is inferred as follows:

$$\dot{x}(t) = \sum_{i=1}^{r} h_{(i,\alpha)}(\omega)[A(i,\alpha)x(t) + W(i,\alpha)\phi(x(t)) + u(t) + w(t)], \tag{2}$$

where $\omega = [\omega_1, \omega_2,\ldots,\omega_s]^T, h_{(i,\alpha)}(\omega) = \psi_{(i,\alpha)}(\omega)/\sum_{j=1}^{r}\psi_{(j,\alpha)}(\omega), \psi_{(i,\alpha)}$ is the membership function of the system with respect to the fuzzy rule $\mathbb{R}^i_\alpha$ $(i = 1,2,\ldots,r)$. $h_{(i,\alpha)}(\omega)$ can be regarded as the normalized weight of each IF-THEN rule and it satisfies $h_{(i,\alpha)}(\omega) \geqslant 0$ and $\sum_{i=1}^{r} h_{(i,\alpha)}(\omega) = 1$. The indicator function is defined as $\xi(t) = [\xi_1(t), \xi_2(t),\ldots,\xi_N(t)]^T$, where $\xi_k(t) = 1$ when the neural network is described by the k-th mode $(A(i,k), W(i,k))$, and $\xi_k(t) = 0$ otherwise $(k = 1,2,\ldots,N)$. This indicator function can be used to derive the model of the T–S fuzzy switched Hopfield neural networks (2) as

$$\dot{x}(t) = \sum_{k=1}^{N}\sum_{i=1}^{r}\xi_k(t)h_{(i,k)}(\omega)[A(i,k)x(t) + W(i,k)\phi(x(t)) + u(t) + w(t)], \tag{3}$$

where $\sum_{k=1}^{N}\xi_k(t) = 1$ is satisfied under all switching rules. The following finite horizon cost with a cross term is associated with the T–S fuzzy switched Hopfield neural network (3):

$$J(x(t_0), t_0, t_1) = \int_{t_0}^{t_1}\left\{\begin{bmatrix} x^T(t) & u^T(t)\end{bmatrix}\begin{bmatrix} Q & S \\ S^T & R\end{bmatrix}\begin{bmatrix} x(t) \\ u(t)\end{bmatrix} - \gamma^2 w(t)^T w(t)\right\}dt + x^T(t_1)Q_f x(t_1), \tag{4}$$

where

$$\begin{bmatrix} Q & S \\ S^T & R\end{bmatrix} \geqslant 0, \quad Q \geqslant 0, \quad R > 0, \quad Q_f = Q_f^T > 0, \tag{5}$$