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State estimation of neural networks with both time-varying delays and norm-bounded parameter uncertainties via a delay decomposition approach

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ABSTRACT

This paper is concerned with the state estimation problem for neural networks with both time-varying delays and norm-bounded parameter uncertainties. By employing a delay decomposition approach and a convex combination technique, we obtain less conservative delay-dependent stability criteria to guarantee the existence of desired state estimator for the delayed neural networks. Finally, numerical examples are presented to demonstrate the effectiveness of the proposed approach.

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1. Introduction

In the past few years, neural networks (*NNs*) have received considerable attention owing to their applications in various areas such as signal processing, associative memory, classification of patterns and so on. It has been well known that time delays are frequently encountered in electronic neural networks due to the unavoidable finite switching speed of amplifiers, meanwhile, time delay is a source of instability and oscillatory response of networks. So the issue of stability analysis of neural networks with time delay attracts many researchers and a number of remarkable results have been built up in the open literature [1–4,8–17].

Since only partial information about the neuron states in relatively large scale neural networks is available in the network output in many practical applications, it is of great important and practical significance to study the state estimation problem of neural networks. Ahn et al. in [18–22] dealt with the state estimation problem for the switched neural networks (*SNNs*) with time-invariant delay. However, since time delay is not just a fixed value in practical implementation of neural networks, the research on the state estimation of neural networks with time-varying delays has been widely investigated [24–27,29–31,33–36]. The main objective of the state estimation problem is to estimate the neuron states with available output measurements such that the dynamics of the error-state system is globally stable. In [30], Wang et al. first studied the problem of the state estimator for delayed neural networks and derived some delay-independent condition. Generally speaking, the delay-dependent stability criteria, which include information on the size of delays, are less conservative than delay-independent ones when the time-delay is small. Therefore, a growing number of works address the problem of finding sufficient delay-dependent state estimation conditions to ensure the stability of delayed neural networks

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[24–27,29,31,33–36]. In recent years, several kinds of approaches are proposed to analyze the stability of dynamics of the error-state system. For example, the Jensen integral inequality approach was utilized to reduce the conservatism in [25,35], whose advantage was that it could provide a simple form of stability conditions with fewer variables. Approaches introducing free-weighting matrices were used to discuss the state estimation problem for delayed neural networks [27,34–36]. It is noted that the proposed criterion in [27] was formulated as a matrix inequality, rather than an LMI. That is a nonlinear programming problem which is generally difficult to be solved. A delay partition approach was proposed in [26,31] to derive some delay-dependent criteria. However, the criterion was addressed in [26] under the precondition that the time-derivative of the delay was strictly smaller than one. In addition, while dealing with the time-derivative of Lyapunov–Kraovskii (LK) functional a few useful terms were neglected which may lead to considerable conservativeness.

On the other hand, the network parameters of a neural system depend on certain resistance and capacitance values that include uncertainties, which may lead to the difficulty and complexity of state estimation. Thus, it is necessary to study state estimation for uncertain neural networks. Motivated by the above observations, in this paper, we study the state estimation problem of neural networks with time-varying delay and parametric uncertainties. In order to obtain more effective stability criteria, we firstly improve the delay decomposition approach by dividing the time-varying delay interval $[-h(t), 0]$ into multiple time-varying segments, which is clearly more general compared with some previous delay decomposition approaches [5,6,26]. Then, the upper bound of the derivative of the Lyapunov–Kraovskii (LK) functional can be expressed as a convex combination with respect to the delay. Next, based on the Lyapunov stability theory and free-weighting matrix approach, the improved delay-dependent stability criteria are derived in terms of LMIs, which can be verified easily by means of Matlab LMI Toolbox [28]. Finally, numerical examples are given to indicate significant improvements over the existing results.

Notation: Throughout this paper, T and -1 stand for the transpose and the inverse of the matrix, respectively; $\Re^n$ is the n-dimensional Euclidean space; $\Re^{n\times m}$ is the set of all $n \times m$-dimensional matrices; $P > 0$ means that P is positive definite Matrices; $|\cdot|$ is the Euclidean norm in $\Re^n$; I is an identity matrix with proper dimension; $diag\{\cdots\}$ denotes a block-diagonal matrix, and the symmetric terms in a symmetric matrix are denoted by $*$., e.g., $\begin{bmatrix} X & Y \\ * & Z \end{bmatrix} = \begin{bmatrix} X & Y \\ Y^T & Z \end{bmatrix}$. Matrices, if not explicitly stated, are assumed to have compatible dimensions.

2. Systems formulation and preliminaries

As in [18–20], switched neural networks (*SNNs*) with time-invariant delay is represented by the following differential equation:

$$\dot{u}(t) = -A(\alpha)u(t) + W_1(\alpha)\tilde{g}(u(t-h)) + J, \tag{1}$$

where α is a switching signal which takes its values in the finite set $\mathfrak{T} = \{1, 2, \ldots, N\}$. It is known that the individual subsystems of the switched neural networks (*SNNs*) are a set of neural networks (*NNs*). That is to say, when $N = 1$, the switched neural networks (*SNNs*) (1) degenerates into the following general neural networks.

$$\dot{u}(t) = -Au(t) + W_1\tilde{g}(u(t-h)) + J. \tag{2}$$

In the following, we will extend system (2) to the following model which is a continuous-time *NNs* with both time-varying delay and norm-bounded parameter uncertainties

$$\dot{u}(t) = -A(t)u(t) + W_0(t)\tilde{g}(u(t)) + W_1(t)\tilde{g}(u(t-h(t))) + J \tag{3}$$

and

$$A(t) = A + \triangle A(t), \tag{4}$$

$$W_0(t) = W_0 + \triangle W_0(t), \tag{5}$$

$$W_1(t) = W_1 + \triangle W_1(t), \tag{6}$$

where $u(t) = [u_1(t), u_2(t), \ldots, u_n(t)]^T \in \Re^n$ is the state vector associated with n neurons, $A = diag\{a_1, a_2, \ldots, a_n\} \in \Re^{n\times n}$ is a diagonal matrix with positive entries $a_i > 0 (i = 1, 2, \ldots, n)$. The matrices $W_0 = (w_{ij}^0)_{n\times n} \in \Re^{n\times n}$ and $W_1 = (w_{ij}^1)_{n\times n} \in \Re^{n\times n}$ are, respectively, the connection weight matrix and the delayed connection weight matrix. $\triangle A(t)$, $\triangle W_0(t)$ and $\triangle W_1(t)$ are the time-varying parameter uncertainties, which are assumed to be of the form

$$\triangle A(t) = HF(t)E_1, \tag{7}$$

$$\triangle W_0(t) = HF(t)E_2, \tag{8}$$

$$\triangle W_1(t) = HF(t)E_3, \tag{9}$$

where H and $E_i (i = 1, 2, 3)$, are known real constant matrices, and $F(\cdot)$ are unknown time-varying matrix function satisfying

$$F^T(t)F(t) \leqslant I. \tag{10}$$

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