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Letters

Robust state estimation for discrete-time neural networks with mixed time-delays, linear fractional uncertainties and successive packet dropouts

Xiu Kan [a], Huisheng Shu [b], Zhenna Li [c]

[a] College of Electronic and Electrical Engineering, Shanghai University of Engineering Science, Shanghai 201620, China
[b] School of Science, Donghua University, Shanghai 200051, China
[c] School of Information Science and Technology, Donghua University, Shanghai 200051, China

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ABSTRACT

This paper is concerned with the robust state estimation problem for a class of discrete-time delayed neural networks with linear fractional uncertainties (LFUs) and successive packet dropouts (SPDs). The mixed time delays (MTDs) consisting of both discrete time-delays and infinite distributed delays enter into the model of the addressed neural networks. A Bernoulli distributed white sequence with a known conditional probability is introduced to govern the random occurrence of the SPDs. The main purpose of the problem under consideration is to design a state estimator such that the dynamics of the estimation error is globally asymptotically stable in the mean square. By using stochastic analysis and Lyapunov stability theory, the desired state estimator is designed to be robust against LFUs and SPDs. Finally, a simulation example is provided to show the effectiveness of the proposed state estimator design scheme.
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1. Introduction

In the past decades, neural networks including Hopfield neural networks, bidirectional associative neural networks, cellular neural networks, as well as Cohen–Grossberg neural networks have been widely investigated. This is mainly due to the extensive applications in various areas such as pattern recognition, affine invariant matching, associative memory, model identification, and combinational optimization. As is well known, these applications highly rely on the dynamical behaviors of the neural networks. Therefore, the stability analysis issue for neural networks has drawn a great deal of attention and considerable research efforts have been made in this area. For instance, by utilizing a combination of the comparison principle, the theory of monotone flow and the monotone operator, some sufficient conditions ensuring existence, uniqueness and global exponential stability of the periodic solution have been derived in [1] for a class of neural networks. In [20], a set of necessary and sufficient conditions has been addressed for the global exponential stability of a class of generic discrete-time recurrent neural networks by means of the uncovered conditions. The globally asymptotic stability analysis problem has been dealt with in [22] for a class of uncertain stochastic Hopfield neural networks with discrete and distributed time-delays in terms of Lyapunov theory.

It is well known that the state estimation is one of the foundational problems in dynamics analysis for complex systems including recurrent neural networks, complex networks, genetic regulatory networks as well as general engineering systems. Over the past few decades, a lot of effective approaches have been proposed in this research area, see e.g. [3,5,6,12,21]. In particular, since modeling errors and incomplete statistical information are often encountered in real-time applications, robust state estimation schemes have recently received considerable research attention in order to improve the robustness. On the other hand, time delays are often unavoidably encountered due to the finite speeds of signals switching and transmission between neurons, which may cause undesirable dynamic network behaviors such as oscillation and instability, see e.g. [9,14,18,23]. So far, two types of time delays, namely discrete and distributed time delays have gained considerable research attention. For example, the state estimation problem has been investigated in [14] for a class of discrete-time neural networks with Markovian jumping parameters as well as mode-dependent mixed time-delays. More recently, the robust H_∞ state estimation problem has been studied in [23] for a general class of uncertain discrete-time stochastic neural networks with probabilistic measurement delays.

Owing to unreliable measurements or network congestion, packet dropouts (or missing measurements), viewed as an often occurred network-induced problem, have drawn considerable research attention during the past few years, see e.g. [2,4,8,16,17,19]. For example, the distributed finite-horizon

E-mail address: xkan1031@gmail.com (X. Kan).

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filtering problem has been proposed in [4] for a class of discrete time-varying systems with randomly varying nonlinearities over lossy sensor networks involving quantization errors and SPDs. In [16], the optimal H_2 filtering problem for linear systems with multiple packet dropouts has been tackled. The robust H_∞ finite-horizon filtering problem has been investigated in [17] for discrete time-varying stochastic systems with norm-bounded uncertainties, multiple randomly occurred sector-nonlinearities and SPDs. In [19], the optimal full-order linear filter in the linear minimum variance sense has been designed for discrete-time stochastic linear systems with multiple packet dropouts. It is worth mentioning that the missing measurement problem in the neural networks has not been fully investigated up to now. Therefore, we aim to study the state estimation problem for neural networks with SPDs.

In addition, due to the modeling errors, parameter drifting or fluctuation, uncertainties occur so frequently that may lead to instability and poor performance of the neural networks. Parameter uncertainties have been mainly categorized as norm-bounded uncertainties and interval uncertainties, while the interval type can be usually transformed into the norm-bounded type. For these two types of uncertainties, the state estimation problem and stability analysis have been investigated in [25,26] for neural networks. It should be pointed out that a more general kind of uncertainties, i.e., LFUs, have been proposed in [7,24] that include the common norm-bounded uncertainties as a special case. In [10], the state estimation problem has been first investigated for a class of discrete-time neural networks with such LFUs and sensor saturations. The stability property has been studied for generalized static neural networks with LFUs in [11]. Nevertheless, very little research effort has been made to account for delayed neural networks with LFUs and SPDs. With hope to shorten such a gap, in this paper, we are motivated to design an estimator for a class of delayed neural networks subject to MTDs, LFUs and SPDs.

Summarizing the discussions made above, the main aim of this paper is to specifically deal with the state estimation problem for a class of discrete-time neural networks with LFUs, MTDs and SPDs. The main contributions of this paper are threefold. (1) SPDs are used to model a class of missing measurements in the context of neural networks, whose occurrence is governed by a specified Bernoulli distribution. (2) LFUs are utilized to describe the parameter uncertainties of the discrete-time neural networks with MTDs. (3) The designed estimator is expected to be robust against LFUs as well as SPDs, and ensure that the error dynamics is globally asymptotically stable in the mean square. The rest of this paper is outlined as follows. In Section 2, the discrete-time delayed neural networks with LFUs and SPDs are introduced. Moreover, the problem under consideration is formulated. In Section 3, by employing the Lyapunov stability theory, some sufficient conditions are established in the form of linear matrix inequalities (LMIs) and the explicit expression of the estimator gain is given. A simulation example is given in Section 4 to demonstrate the effectiveness of the main results obtained.

Notation: The notation used here is fairly standard except where otherwise stated. $\mathbb{N}^+$ stands for the set of nonnegative integers. $\mathbb{R}^n$ and $\mathbb{R}^{n\times m}$ denote, respectively, the n dimensional Euclidean space and the set of all $n\times m$ real matrices. For a vector $x=(x_1,x_2,\ldots,x_n)^T\in\mathbb{R}^n$, $|x|$ is the Euclidean norm. The notation $X\geq Y$(respectively, $X>Y$), where X and Y are real symmetric matrices, means that $X-Y$ is positive semi-definite (respectively, positive definite). M^T represents the transpose of the matrix M. I denotes the identity matrix of compatible dimension. If A is a matrix, $\lambda_{\min}(A)$ (respectively, $\lambda_{\max}(A)$) stands for the smallest (respectively, largest) eigenvalue of A. diag$\{\cdots\}$ stands for a block-diagonal matrix. The $*$ in a matrix is used to denote term that is induced by symmetry. Moreover, let $(\Omega,\mathcal{F},\text{Prob})$ be a probability space, where Prob, the probability measure, has total mass 1. $\mathbb{E}\{x\}$ stands for the expectation of the stochastic variable x with respect to the given probability measure Prob. The symbol $\otimes$ denotes the Kronecker product. Matrices, if they are not explicitly specified, are assumed to have compatible dimensions.

2. Problem formulation and preliminaries

Consider a discrete-time n-neuro neural network with MTDs described as follows:

$$\begin{cases} x(k+1)=A(k)x(k)+B_1(k)f(x(k))+B_2(k)g(x(k-\tau(k))) \\ \qquad +B_3(k)\sum_{d=1}^{+\infty}\mu_d h(x(k-d))+D(k)x(k)\omega(k) \\ \tilde{y}(k)=C(k)x(k) \\ x(s)=\phi(s), \quad s=-\tau_M,-\tau_M+1,\ldots,-1,0 \end{cases} \tag{1}$$

where $x(k)=[x_1(k),x_2(k),\ldots,x_n(k)]^T\in\mathbb{R}^n$ is the state vector of the neural network; $\tilde{y}(k)\in\mathbb{R}^m$ is the measurement output vector; the nonlinear vector-valued functions $f(x(k))=[f_1(x_1(k)),f_2(x_2(k)),\ldots,f_n(x_n(k))]^T$, $g(x(k)))=[g_1(x_1(k)),g_2(x_2(k)),\ldots,g_n(x_n(k))]^T$ and $h(x(k))=[h_1(x_1(k)),h_2(x_2(k)),\ldots,h_n(x_n(k))]^T$ are the neuron activation functions; the positive integer $\tau(k)$ describes the time-varying delay satisfying $0<\tau_m\leq\tau(k)\leq\tau_M$, where τ_m and τ_M are known positive integers representing the minimum and maximum delays respectively; $\phi(s)$ is a given initial condition sequence; $\omega(k)$ is a scalar Wiener process (Brownian motion) on $(\Omega,\mathcal{F},\text{Prob})$ with

$$\mathbb{E}\{\omega(k)\}=0, \quad \mathbb{E}\{\omega^2(k)\}=1, \quad \mathbb{E}\{\omega(i)\omega(j)\}=0 \quad (i\neq j). \tag{2}$$

The constant $\mu_d\geq 0$ satisfies the following convergence condition:

$$\bar{\mu}=\sum_{d=1}^{+\infty}\mu_d \quad \text{and} \quad \sum_{d=1}^{+\infty}d\mu_d<+\infty. \tag{3}$$

The matrices $A(k)=A+\Delta A(k)$, $B_1(k)=B_1+\Delta B_1(k)$, $B_2(k)=B_2+\Delta B_2(k)$, $B_3(k)=B_3+\Delta B_3(k)$, $C(k)=C+\Delta C(k)$ and $D(k)=D+\Delta D(k)$ are bounded matrices containing parameter uncertainties $\Delta A(k)$, $\Delta B_1(k)$, $\Delta B_2(k)$, $\Delta B_3(k)$, $\Delta C(k)$ and $\Delta D(k)$ that satisfy the following conditions:

$$\begin{bmatrix} \Delta A(k) & \Delta B_1(k) & \Delta B_2(k) \\ \Delta C(k) & \Delta D(k) & \Delta B_3(k) \end{bmatrix}=\begin{bmatrix} M_1 \\ M_2 \end{bmatrix}\Sigma(k)(I-\mathcal{J}\Sigma(k))^{-1}[N_1\ N_2\ N_3], \tag{4}$$

$$\mathcal{J}^T\mathcal{J}<I, \quad \Sigma^T(k)\Sigma(k)\leq I, \quad \forall k\in\mathbb{N}^+ \tag{5}$$

where $A=\text{diag}\{a_1,a_2,\ldots,a_n\}$ and B_1, B_2, B_3, C, D, H, M_i $(i=1,2)$ and N_i $(i=1,2,3)$ are known constant matrices with appropriate dimensions, and $\Sigma(k)$ denotes the unknown matrix functions with Lebesgue measurable elements.

Remark 1. In the neural network model (1), the conditions (4) and (5) are referred to as the admissible conditions. Note that this kind of parametric uncertainties means LFUs. As explained in Section 1, the LFUs are more general than the common uncertainties such as the norm-bounded type [22] and the interval type [25]. Notice that when $\mathcal{J}=0$, the linear fractional parametric uncertainties reduce to the norm-bounded ones. Also, interval uncertainties can be viewed as the special case of norm-bounded ones. Therefore, it is more appropriate to use the linear fractional form to describe the parameter uncertainties in practical neural networks.

The nonlinear activation functions $f(\cdot)$, $g(\cdot)$ and $h(\cdot)$ are assumed to be continuous and satisfy $f(0)=0$, $g(0)=0$, $h(0)=0$ and the following sector-bounded conditions, namely for $\forall x,y\in\mathbb{R}^n$:

$$[f(x)-f(y)-U_1(x-y)]^T[f(x)-f(y)-U_2(x-y)]\leq 0, \tag{6}$$

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