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Finite-time state estimation for delayed periodic neural networks over multiple-packet transmission☆

Xiao-Meng Li[a], Yun Chen[a,*], Jun-Yi Li[b]

[a] Key Lab for IoT and Information Fusion Technology of Zhejiang, Institute of Information and Control, Hangzhou Dianzi University, Hangzhou 310018, China
[b] Guangdong Key Laboratory of IoT Information Technology, School of Automation, Guangdong University of Technology, Guangzhou 510006, China

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ABSTRACT

In this paper, the problem of finite-time state estimation for delayed periodic neural networks over multiple-packet transmission is addressed. The components of measurement output are separately transmitted by multiple-packet transmission, and the randomly occurring packet dropouts of different channels are described by mutually independent Bernoulli processes. In order to improve the robustness of the estimator, a non-fragile estimator is designed. In addition, some sufficient criteria are given to ensure that the estimation error system is stochastically finite-time stable and stochastically finite-time bounded, and the gains of non-fragile estimator are then derived based on these results. Finally, simulation results are provided to illustrate the effectiveness of the proposed estimator design approach.

1. Introduction

Neural networks (NNs) have been successfully applied in numerous areas in the past several decades, such as signal processing, pattern classification, combinational optimization, and so on [1–4]. It is known that delays are often unavoidably encountered in NNs, which may lead to the reduction of the performance or even the deterioration of system stability. Thus, it is important and necessary to consider the effect of delays on the dynamical behaviors of NNs [5–8]. In recent years, state estimators have been designed for NNs with delay to obtain the neurons states [9–13]. However, in practical realizations of state estimator, the gains of the estimators are generally unideal, and the parametric variations of the estimator gains should be taken into account. As such, non-fragile estimator design problem for NNs has received a large amount of attention [14–16]. Non-fragile $l_2 - l_\infty$ state estimators have been designed for discrete-time NNs with Markovian jumping parameters [14,15]. The problem of state estimation for discrete-time NNs with delay has been discussed in [16].

Periodic dynamical equations can be used to describe many real-world systems, that repeat the dynamical characteristics in certain periods [17–19]. Up to now, periodic behaviors of NNs have been successfully applied in associative memories [20], robot motion [21], pattern recognition [22], etc. It is worth noting that the problem of continuous-time periodic NNs with delay has been addressed by [23–25]. In [24], the global exponential stability condition has been obtained for continuous-time delay periodic NNs. The periodic behaviors of continuous-time memristor-based NNs with leakage and time-varying delays have been investigated in [25]. Most recently, [26] has dealt with the state estimation problem for discrete-time periodic NNs with uncertain weighting matrices and Markovian jumping channel states.

With the wide application of networked control systems, network-induced problems such as packet dropouts have attracted numerous interests [27–32]. Most of the existing results concerning packet dropouts are established based on the assumption that data are transmitted through a single packet which is called as single-packet transmission. However, in many practical applications, sensors/actuators are often spatially distributed over a large physical area, and a large amount of data must be split into multiple packets to be transmitted because of the bandwidth and packet size constraints. Therefore, it is of practical significance to adopt multiple-packet transmission strategy for networked control systems [33–35]. In such transmission strategy, the data are separately transmitted by different packets [33] with mutually independent packet dropout rates. In [34], the necessary and sufficient stability conditions of discrete-time networked control systems under a multiple-packet transmission policy have been obtained. An H_∞ controller has been constructed for networked control systems

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* Corresponding author.
E-mail addresses: yunchen@hdu.edu.cn, cloudscy@msn.com (Y. Chen).

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with packet dropouts over multiple-packet transmission in [35]. However, the state estimator design problem for periodic NNs over multiple-packet transmission has not been considered.

As is well known, stability concept is of great significance in systems and control theory. Most of the relevant literatures have only focused on system stability over infinite time horizon. However, in many practical situations, it is valuable to study the system stability over a given time domain [36–38]. Recently, increasing research attention has been paid to finite-time analysis and synthesis for NNs [39–42]. Finite-time boundedness of discrete Markovian jumping NNs with uncertainties and time delays has been analyzed [39]. The finite-time state estimator design methods have been proposed for NNs with delay [40,41]. The finite-time non-fragile $l_2 - l_\infty$ state estimation issue has been investigated for discrete-time Markovian jump NNs with unreliable communication links (sensor nonlinearities, delays and packet dropouts) in [42]. Nevertheless, due to the complexity and difficulty resulting from the existences of periodic properties, multiple-packet transmission ways, estimator gain uncertainties, and time delays, the problem of finite-time non-fragile state estimation for delayed periodic NNs over multiple-packet transmission has not been fully investigated yet.

Motivated by the aforementioned analysis, the main objective of this paper is to make the first attempt to design a finite-time non-fragile estimator for delayed periodic NNs over multiple-packet transmission. By applying the finite-time stability analysis method, some sufficient conditions are provided to ensure the stochastic finite-time stability and the stochastic finite-time boundedness of the estimation error system (EES). And the non-fragile estimator gains can be explicitly determined by solving some inequalities. Finally, a numerical example is provided to illustrate the effectiveness of the proposed method. The main contributions of this paper are summarized as follows.

(1) Under multiple-packet transmission strategy, the period-dependent packet dropouts of the measurement are proposed, which have not been considered in the existing papers concerning multiple-packet transmission [34,35].

(2) The finite-time state estimation issue over multiple-packet transmission for delayed periodic NNs is investigated to guarantee the stochastic finite-time property of the EES.

(3) A non-fragile state estimator is designed for delayed periodic NNs to ensure that the EES is stochastically finite-time bounded (SFTB) against the estimator gain uncertainties and exogenous disturbances.

Notations: The notations employed in this paper are quite standard. $\mathbb{Z}^+$ represents the set of positive integers. $\mathbb{R}^n$ and $\mathbb{R}^{n\times m}$ represent n-dimensional Euclidean space and the set of $n\times m$ real matrices, respectively. I stands for the identity matrix of appropriate dimension. diag$\{\ldots\}$ denotes a block diagonal matrix. The symbol $*$ represents the elements deduced by symmetry; the notation X^T stands for the transposition of matrix X; matrix $X_{\varsigma(k)}$ denotes an M-periodic matrix with $M\in\mathbb{Z}^+$. For a symmetric matrix $\mathcal{P}$, $\mathcal{P}\geq 0$ (>0) means that $\mathcal{P}$ is positive semi-define (or positive define), and $\mathcal{X}\geq\mathcal{Y}$ ($\mathcal{X}>\mathcal{Y}$) means $\mathcal{X}-\mathcal{Y}\geq 0$ (>0). $\mathbb{P}\{a(k)=b\}$ stands for the occurrence probability of event $a(k)=b$. The expectation of a random variable $a(k)$ is denoted by $\mathbb{E}\{a(k)\}$. mod(m, n) represents the non-negative remainder after division of $m\in\mathbb{Z}^+$ by $n\in\mathbb{Z}^+$.

2. Problem formulation and preliminaries

Consider the following M-periodic NNs with delay:

$$\begin{cases}\mathbf{x}(k+1)=A_{\varsigma(k)}\mathbf{x}(k)+E_{\varsigma(k)}\mathbf{g}(\mathbf{x}(k))+F_{d,\varsigma(k)}\mathbf{g}(\mathbf{x}(k-d))+B_{\varsigma(k)}\mathbf{w}(k)\\ \mathbf{y}(k)=C_{\varsigma(k)}\mathbf{x}(k)+D_{\varsigma(k)}\mathbf{w}(k)\\ \mathbf{x}(k)=\psi(k),\quad -d\leq k\leq 0,\end{cases}\tag{1}$$

where $\mathbf{x}(k)\in\mathbb{R}^n$ is the state vector; $\mathbf{y}(k)\in\mathbb{R}^m$ is the output vector; $\psi(k)$ is the initial condition, and $d>0$ is an integer representing the delay; $A_{\varsigma(k)}$, $B_{\varsigma(k)}$, $C_{\varsigma(k)}$, $D_{\varsigma(k)}$, $E_{\varsigma(k)}$, $F_{d,\,\varsigma(k)}$ are M-periodic known constant matrices with appropriate dimensions where $A_{\varsigma(k)}=\text{diag}\{a_{1\varsigma(k)},a_{2\varsigma(k)},\ldots,a_{n\varsigma(k)}\}\in\mathbb{R}^{n\times n}$; $\mathbf{g}(\mathbf{x}(k))=[g_1(x_1(k))\ \ g_2(x_2(k))\ \ \ldots\ \ g_n(x_n(k))]^T\in\mathbb{R}^n$ is the neural activation function vector. $E_{\varsigma(k)}$ and $F_{d,\,\varsigma(k)}$ are the connection weight matrix and delayed connection weight matrix, respectively. $\mathbf{w}(k)\in\mathbb{R}^q$ is the exogenous disturbance satisfying

$$\sum_{k=0}^{N}\mathbf{w}^T(k)\mathbf{w}(k)\leq\delta_w^2.$$

Moreover, the M-periodic index $\varsigma(k)\in\mathcal{M}\triangleq\{1,2,\ldots,M\}$ can be defined as follows:

$$\varsigma(k)\triangleq\begin{cases}\text{mod}(k,M)+1, & k\geq 0\\ \text{mod}(k+M,M)+1, & \text{otherwise.}\end{cases}$$

Furthermore, the activation function $\mathbf{g}(\cdot)$ in (1) satisfies the following assumption:

Assumption 1. [6] The activation function $g_i(\cdot)$ in (1) is bounded, continuous, non-monotonic, and there exist known constants ρ_i^+ and ρ_i^-, such that

$$\rho_i^-\leq\frac{g_i(\pi_1)-g_i(\pi_2)}{\pi_1-\pi_2}\leq\rho_i^+$$

holds for all π_1, π_2, and $\pi_1\neq\pi_2$.

Note that ρ_i^+ and ρ_i^- can be positive or negative or zero.

The non-fragile estimator for (1) is with the following form:

$$\begin{aligned}\hat{\mathbf{x}}(k+1)&=A_{\varsigma(k)}\hat{\mathbf{x}}(k)+E_{\varsigma(k)}\mathbf{g}(\hat{\mathbf{x}}(k))+F_{d,\varsigma(k)}\\&\quad\times\mathbf{g}(\hat{\mathbf{x}}(k-d))+(K_{\varsigma(k)}+\Delta K_{\varsigma(k)})\\&\quad\times\theta_{\varsigma(k)}(k)\big(\mathbf{y}(k)-C_{\varsigma(k)}\hat{\mathbf{x}}(k)\big),\end{aligned}\tag{2}$$

where $\hat{\mathbf{x}}(k)\in\mathbb{R}^n$ is estimator state vector; $K_{\varsigma(k)}$ are the estimator gains to be designed; $\Delta K_{\varsigma(k)}$ represent the gain variations of estimator, which satisfy the following norm-bounded multiplicative form:

$$\Delta K_{\varsigma(k)}=M_{\varsigma(k)}H_{\varsigma(k)}(k)N_{\varsigma(k)},\tag{3}$$

where $M_{\varsigma(k)}$, $N_{\varsigma(k)}$ are known M-periodic real constant matrices with appropriate dimensions, and $H_{\varsigma(k)}(k)$ represent unknown M-periodic time-varying matrices satisfying $H^T_{\varsigma(k)}(k)H_{\varsigma(k)}(k)\leq I$.

Remark 1. The estimator gains are susceptible to the exogenous/internal disturbances, which is known as the unexpected fragility of estimator. Such phenomenon should be considered when designing the state estimator. In the past years, the problem of non-fragile estimator design for NNs has been extensively investigated [14–16,42]. The gain uncertainties in (3) are period-dependent, and they reduce to those in [14–16,42] when $M=1$.

Since the measurements are transmitted through unreliable transmission channels, packet dropouts may occur. The following diagonal matrix $\theta_{\varsigma(k)}(k)$ is introduced to describe the packet dropouts:

$$\theta_{\varsigma(k)}(k)=\text{diag}\big\{\theta_{1\varsigma(k)}(k),\theta_{2\varsigma(k)}(k),\ldots,\theta_{m\varsigma(k)}(k)\big\}.$$

Each diagonal element $\theta_{i\varsigma(k)}(k)(i=1,2,\ldots,m)$ is a Bernoulli process with the following properties:

$$\begin{aligned}&\mathbb{P}\big\{\theta_{i\varsigma(k)}(k)=1\big\}=\bar{\theta}_{i\varsigma(k)}\\&\mathbb{P}\big\{\theta_{i\varsigma(k)}(k)=0\big\}=1-\bar{\theta}_{i\varsigma(k)},\end{aligned}\tag{4}$$