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Improved Delay-dependent Robust Stability Analysis for Neutral-type Uncertain Neural Networks with Markovian jumping Parameters and Time-varying Delays

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ABSTRACT

This paper deals with the problem of robust stochastic stability analysis for a class of neutral-type uncertain neural networks with Markovian jumping parameters and time-varying delays. By introducing an novel mode-dependent Augmented Lyapunov-Krasovskii functional with delay partitioning and Wirtinger-based integral inequality techniques, some improved delay-dependent stochastically stable conditions are proposed in the form of LMIs. Numerical simulations are provided to show the effectiveness and less conservatism of the results.

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1. Introduction

In the last few decades, the study of neural networks has shown an increasing research for their wide application in many fields such as pattern recognition, signal processing, optimization problem, knowledge acquisition and so on [1,2]. It is well known that the stability has been proved to be one of the most important behaviors for neural networks, meanwhile, time delay often appears in neural networks due to the signal transmission lags between neurons, and it is frequently the reason of instability and poor performance in neural networks. Therefore, the stability analysis problem of delayed neural networks have received much attention in recent years, and a number of results related to this problem have been published, see, for example, in [3–10]. Furthermore, it is common that the time delay occurs not only in system states or outputs but also in the derivatives of system states, the systems containing the information of past state derivatives are called neutral-type systems. Accordingly, the stability analysis of neutral-type neural networks has also been received considerable attention and lots of works were reported in recent years [11–15].

On the other hand, as an important kind of hybrid systems, Markovian jumping systems have been widely studied in the past decades due to their advantage of modeling many practical dynamic systems, such as manufacturing systems, networked control systems, economics systems, fault-tolerant control systems, etc., and lots of works on stability analysis, controller synthesis and filter design have been focused on the study for Markovian jumping systems [16–21]. Recently, there were lots of research works on the dynamics analysis for delayed neural networks with Markovian jumping parameters have been reported in the literature [22–34]. For example, for neural networks with Markovian jumping parameters and time delays, the problem of stability analysis and passivity analysis have been investigated in [22–24] and [27,28], respectively. And the same problems have been proposed in [29–32] and [33,34] for the neutral-type delayed neural networks with Markovian jumping parameters. It is worth mentioning that, although there are already many works to deal with the problem of dynamic analysis to those neural networks, they are still conservative to some extent, for example, the technique to deal with the cross products in most of those works was Jensen inequality, it will lead to some conservativeness of the achieved results, which leaves great room for further research.

In this paper, the problem of robust stochastic stability in the mean square for neutral-type uncertain neural networks with Markovian jumping parameters and time-varying delays is investigated. By constructing a novel augmented Lyapunov-Krasovskii functional based on the idea of delay partitioning, and using new

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effective techniques(reciprocally convex approach and Wirtinger-based integral inequality), some delay-dependent stochastic stability conditions are obtained in terms of LMIs. Numerical examples are given to show the effectiveness of the achieved criteria.

Notation: Throughout this paper, for symmetric matrices X and Y, the notation $X \geq Y$ (respectively, $X > Y$) means that the matrix $X-Y$ is positive semi-definite (respectively, positive definite); I is the identity matrix with appropriate dimension; M^T represents the transpose of the matrix M; R^n denotes the n-dimensional Euclidean space; $0_{m\times n}$ represents a zero matrix with $m\times n$ dimensions; $\|\cdot\|$ denotes the Euclidean norm for vector or the spectral norm of matrices; $sym(A)$ denotes $A+A^T$; (Ω, F, P) is a probability space, where Ω is the sample space, F is the σ-algebra of subsets of the sample space, and P is the probability measure on F; and $L^2_{F_0}([-h,0]; R^n)$ denotes the family of all F_0- measurable $C([-h,0]; R^n)$-valued random variables $\xi=\{\xi(\theta): -h\leq\theta\leq 0\}$ such that $\sup_{-h\leq\theta\leq 0}\mathcal{E}\{|\xi(\theta)|^2\}<\infty$, where $\mathcal{E}\{\cdot\}$ stands for the expectation operator with respect to some probability measure P. The notations $X>0$ (≥ 0) is used to denote a symmetric positive-definite (positive-semidefinite) matrix. In symmetric block matrices or complex matrix expressions, we use an asterisk $*$ to represent a term that is induced by symmetry, and $diag\{\cdot\}$ stands for a block-diagonal matrix. Matrices, if their dimensions are not explicitly stated, are assumed to be compatible for algebraic operations.

2. System description and preliminaries

Consider the neutral-type neural networks with Markovian jumping parameters and mixed delays

$$\dot{x}(t)=E(r_t,t)\dot{x}(t-\tau_1(t))+A(r_t,t)x(t)+B(r_t,t)f(x(t)) \\ +C(r_t,t)f(x(t-\tau_2(t)))+D(r_t,t)\int_{t-\tau_3(t)}^{t} f(x(s))ds, \quad (1)$$

where $x(t)=[x_1(t),x_2(t),..,x_n(t)]\in R^n$ is the neuron state vector; $f(x(\cdot))=[f_1(x_1(\cdot)),f_2(x_2(\cdot)),\dots,f_n(x_n(\cdot))]^T\in R^n$, is the neuron activation function vectors; $\{r_t, t\geq 0\}$ is a right-continuous Markov process defined on the probability space which takes values in a finite set $\mathcal{N}=\{1,2,\dots,s\}$ with transition probability matrix $\Lambda=(\pi_{ij})$ given by

$$P\{r_{t+\Delta}=j|r_t=i\}=\begin{cases}\pi_{ij}\Delta+o(\Delta) \text{ if } i\neq j,\\ 1+\pi_{ii}\Delta+o(\Delta) \text{ if } i=j,\end{cases} \quad (2)$$

where $\Delta>0$ and $\lim_{\Delta\to 0}o(\Delta)/\Delta=0$, $\pi_{ij}\geq 0$ is the transition rate from i to j if $i\neq j$ and $\pi_{ii}=-\sum_{i\neq j}\pi_{ij}$. The uncertain matrices of the system $E(r_t,t)$, $A(r_t,t)$, $B(r_t,t)$, $C(r_t,t)$, $D(r_t,t)$ denote interconnection weight matrices and can be described by

$$[E(r_t,t)\ A(r_t,t)\ B(r_t,t)\ C(r_t,t)\ D(r_t,t)]=[E(r_t)\ A(r_t)\ B(r_t)\ C(r_t)\ D(r_t)] \\ +G(r_t)J(r_t,t)[N_e(r_t)\ N_a(r_t)\ N_b(r_t)\ N_c(r_t)\ N_d(r_t)], \quad (3)$$

where $A(r_t)=-diag(a_1(r_t),a_1(r_t),\dots,a_n(r_t))$, $E(r_t)$, $B(r_t)$, $C(r_t)$, $D(r_t)$, $G(r_t)$, $N_e(r_t)$, $N_a(r_t)$, $N_b(r_t)$, $N_c(r_t)$ and $N_d(r_t)$ are real constant matrices. For simplicity, for each $r_t=i\in\{1,2,\dots,s\}$, the matrices $A(r_t)$ will be denoted as $A(r_t)=A_i$, $E(r_t)=E_i$, and so on. $J(r(t),t)$ is an unknown time-varying matrix which satisfies

$$J^T(r(t),t)J(r(t),t)\leq I. \quad (4)$$

The time-varying delay $\tau_1(t)$, $\tau_2(t)$ and $\tau_3(t)$ are satisfying

$$0\leq\tau_1^-\leq\tau_1(t)\leq\tau_1^+,\quad \dot{\tau}_1(t)\leq\mu_1, \\ 0<\tau_2^-\leq\tau_2(t)\leq\tau_2^+,\quad \dot{\tau}_2(t)\leq\mu_2, \\ 0\leq\tau_3(t)\leq\tau_3^+. \quad (5)$$

Furthermore, we make the following assumption for the neuron activation functions $f_i(x(\cdot))$.

Assumption 1. The activation functions $f_i(x(\cdot))$ are continuous, bounded and satisfy

$$\gamma_k^-\leq\frac{f_k(\alpha)-f_k(\beta)}{\alpha-\beta}\leq\gamma_k^+,\quad k=1,2,\dots,n. \quad (6)$$

where $f_k(0)=0$, $\alpha,\beta\in R$, $\alpha\neq\beta$, and γ_k^-, γ_k^+ are known real scalars.

In order to obtain our main results, the following definition and lemmas are employed throughout our paper.

Definition 1. The trivial solution (equilibrium point) of the neutral-type neural networks with Markovian jumping parameters (1) is said to be robustly stochastically stable in the mean square, if

$$\lim_{t\to\infty}\mathcal{E}\{||x(t)||^2\}=0, \quad (7)$$

for all admissible uncertainties satisfying (3)–(4).

Lemma 1 ([35]). *Let A, D, E be real constant matrices with appropriate dimensions, matrix F(t) satisfies $F^T(t)F(t)\leq I$. For any $\varepsilon>0$, then*

$$DF(t)E+E^TF^T(t)D^T\leq\varepsilon^{-1}DD^T+\varepsilon E^TE. \quad (8)$$

Lemma 2 ([36]). *For any symmetric definite matrix $M=M^T>0$, scalar $\gamma>0$ and vector function $\omega:[0,\gamma]\to R^m$ such that the integrations in the following are well defined, the following inequality holds*

$$\gamma\int_0^\gamma\omega(\beta)^TM\omega(\beta)d\beta\geq\left(\int_0^\gamma\omega(\beta)d\beta\right)^TM\int_0^\gamma\omega(\beta)d\beta. \quad (9)$$

Lemma 3 ([37]). *For any differential vector function $\xi(t)$ and scalar function $d(t)$ with $0\leq d_1\leq d(t)\leq d_2$, and for any matrices $Z\in R^{n\times n}$, $U\in R^{n\times n}$ with $\left[\begin{smallmatrix}U & Z\\ * & U\end{smallmatrix}\right]\geq 0$, the following inequality always holds*

$$-(d_2-d_1)\int_{t-d_2}^{t-d_1}\dot{\xi}(\alpha)^TU\dot{\xi}(\alpha)d\alpha\leq\eta(t)^T\mathcal{U}\eta(t), \quad (10)$$

where

$$\eta(t)=\left[\xi(t-d_1)^T\ \ \xi(t-d(t))^T\ \ \xi(t-d_2)^T\right]^T$$

$$\mathcal{U}=\begin{bmatrix}-U & U-Z & Z\\ * & -2U+Z+Z^T & U-Z\\ * & * & -U\end{bmatrix}. \quad (11)$$

Lemma 4 ([38]). *Let $f_1,f_2,\dots,f_N:R^m\to R$ have positive values in an open subsets D of R^m. Then, the reciprocally convex combination of f_i over D satisfies*

$$\min_{\{\alpha_i|\alpha_i>0,\sum_i\alpha_i=1\}}\sum_i\frac{1}{\alpha_i}f_i(t)=\sum_i f_i(t)+\max_{g_{i,j}(t)}\sum_{i\neq j}g_{ij}(t) \quad (12)$$

subject to

$$\left\{g_{ij}(t):R^m\to R, g_{ij}(t)=g_{ji}(t),\begin{bmatrix}f_i(t) & g_{ij}(t)\\ g_{ji}(t) & f_j(t)\end{bmatrix}\geq 0\right\}. \quad (13)$$

Lemma 5 ([39]). *For any given positive matrix $Z>0$, the following inequality holds for differentiable function $x(t)$ in $[\alpha,\beta]\to R^n$:*

$$\int_\alpha^\beta\dot{x}^T(s)Z\dot{x}(s)ds\geq\frac{1}{\beta-\alpha}\delta^T\widehat{Z}\delta, \quad (14)$$

where

$$\delta=\begin{bmatrix}x(\beta)-x(\alpha)\\ x(\beta)+x(\alpha)-\frac{2}{\beta-\alpha}\int_\alpha^\beta x(s)ds\end{bmatrix}$$

and $\widehat{Z}=diag(Z,3Z)$.

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