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Delay-dependent Passivity of Impulsive Cellular Neural Networks with Mixed Time-varying Delays

Jingfeng Wang[a,b,*], Lixin Tian[a,c]
[a]Nonlinear Scientific Research Center, Jiangsu University, Zhenjiang, Jiangsu, 212013. P.R. China
[b]School of Mathematical Sciences, Huaiyin Normal University, Huaian, Jiangsu, 22300. P.R. China
[c]School of Mathematical Sciences, Nanjing Normal University, Nanjing, Jiangsu, 210046. P.R. China
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Abstract: The problem of delay-dependent passivity analysis is investigated for impulsive cellular neural networks with discrete and distributed time-varying delays. By use of Lyapunov-Krasovskii function and matrix inequality approach, some delay-dependent sufficient conditions are obtained to guarantee the passivity of the considered system. Two numerical examples are provided to demonstrate the effectiveness of the proposed result.

Keywords: passivity ; impulsive ; cellular neural networks ; Lyapunov function.

1 Introduction

It is well known that cellular neural networks (CNN) were originally introduced by Chua and Yang in [1,2]. Due to their extensive practical applications, considerable attention has been devoted to this class of neural networks, for example ,[3-8] . In reality , however, time delays in neural networks can caused by neural processing and signal transmission that may lead to oscillation and instability [3-7,12-18]. At the same time, in hardware implementation of neural networks, component's faults, switching phenomenon, frequency change or sudden noise and so on often cause the states of neural networks abrupt change at certain instants. Such neural networks are referred to as impulsive neural networks, which are modeled by impulsive differential equations [7-9]. Therefore, it is necessary to consider the characteristics of cellular neural networks with both time-delay effect and impulsive effect.

On the other hand, the passivity theory originated from circuit theory plays an important role in the analysis and design of linear and nonlinear systems, especially for high-order systems[10]. It should be pointed out that the essence of the passivity theory is that the passivity properties of a system can keep the system internal stability[11]. Recently, considerable attention has also been paid to the passivity analysis of neural networks with time delays [4,7,12-17]. However, to the best of our knowledge, the passivity conditions for impulsive cellular neural networks with time-varying delays have not been fully investigated, and there is still much room left for further investigation. This constitutes the motivation for the present research.

Motivated by the above discussions, we study the problem of delay-dependent passivity for impulsive cellular neural networks with mixed time-varying delays. The aim of this paper is to derive some new sufficient conditions for the system. The method is based on Lyapunov-Krasovskii functional and matrix inequality approach. We also provide two numerical examples to demonstrate the effectiveness of the proposed result.

$Notation$: The notations used throughout this paper are quite standard. R^n and $R^{m\times n}$ denote the n -dimensional Euclidean space and the set of all $m\times n$ real matrices, respectively. The notation $X>Y$ ($X\geq Y$) , where X and Y are symmetric matrices, means that $X-Y$ is positive definite (positive semidefinite). I and 0 represent the identity matrix and a zero matrix, respectively. The superscript "T " represents the transpose, and diag$\{\cdots\}$ stands for a block-diagonal

*Corresponding author. *E-mail address*: jfwang0101@126.com

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matrix. For an arbitrary matrix B and two symmetric matrices A and C ,

$$\begin{pmatrix} A & B \\ * & C \end{pmatrix}$$

denote a symmetric matrix, where " $*$ " denotes the term that is induced by symmetry matrices, if their dimensions are not explicitly stated, these are assumed to have compatible dimensions for algebraic operations.

2 Preliminaries

Consider the following impulsive cellular neural networks with mixed time-varying delays:

$$\begin{cases} \dot{x}(t) = -Ax(t) + B_0 g(x(t)) + B_1 g(x(t-h(t))) + B_2 \int_{t-\tau(t)}^{t} g(x(s))ds + u(t) \quad t \neq t_k, \\ x(t_k^+) = \lambda_k(x(t_k^-)) \quad k \in N, \\ y(t) = g(x(t)) + g(x(t-h(t))) + u(t), \end{cases} \tag{1}$$

where $x(t) = [x_1(t), x_2(t), \cdots, x_n(t)]^T \in R^n$ is the neuron state vector at time t, n denotes the number of neurons in a neural network, $y(t) = [y_1(t), y_2(t), \cdots, y_n(t)]^T \in R^n$ is the output vector of neuron networks, $g(x(t)) = [g_1(x_1(t)), g_2(x_2(t)), \cdots, g_n(x_n(t))]^T \in R^n$ denotes the activation function and satisfies $g(x(0)) = 0$, $A = diag(a_1, a_2, \cdots, a_n)$ is a diagonal matrix with positive entries, $B_0 = (b_{ij}^0)_{n\times n}$, $B_1 = (b_{ij}^1)_{n\times n}$, $B_2 = (b_{ij}^2)_{n\times n}$ are the interconnection matrices representing the weight coefficients of the neurons, $u(t) = [u_1(t), u_2(t), \cdots, u_n(t)]^T \in R^n$ is the external input vector to neuron networks, $h(t) = [h_1(t), h_2(t), \cdots, h_n(t)]^T \in R^n$ denotes the discrete time-varying delays which satisfy $0 \le h_j(t) \le h$, $j = 1, 2, \cdots, n$, if $h_j(t)$ are unbounded, then let $h = +\infty$, $\tau(t) = [\tau_1(t), \tau_2(t), \cdots, \tau_n(t)]^T \in R^n$ denotes the distributed time-varying delays which satisfy $0 \le \tau_j(t) \le \tau$, $j = 1, 2, \cdots, n$, where τ is a positive constant . $t_1, t_2, \cdots$ is a sequence of strictly increasing impulsive moments, $\lambda_k \in R$ represents the strength of impulsive. Assume that $x(t)$ is right continuous at $t = t_k$ i.e. $x(t_k) = x(t_k^+)$.

The initial condition of impulsive networks (1) is

$$x(s) = \varphi(s)\,, s \in [-\mu, 0]\,, \tag{2}$$

where $\varphi(s) = \varphi(s) = [\varphi_1(s), \varphi_2(s), \cdots, \varphi_n(s)]^T$, $\varphi(s)$ is a real-valued continuous function on $[-\mu, 0]$, $\mu = \max\{h, \tau\}$. Let $\varphi = 0$.

Throughout this paper, we shall use the following assumptions, definition and lemmas.

Assumption 1 *The activation functions $g_i(\cdot)(i = 1, 2, \cdots, n)$ in (1) are continuous and bounded, and there exist constants $L_i(i = 1, 2, \cdots, n)$ such that*

$$|g_i(\alpha) - g_i(\beta)| \le L_i \,|\alpha - \beta|\,, \tag{3}$$

where $g_i(0) = 0, \alpha, \beta \in R$, and denote $L = \max\{L_1, L_2, \cdots, L_n\}$.

Assumption 2 *The activation functions $g_i(\cdot)(i = 1, 2, \cdots, n)$ in (1) are continuous and bounded, and there exist constants $K_i(i = 1, 2, \cdots, n)$ such that*

$$0 \le \frac{g_i(\alpha) - g_i(\beta)}{\alpha - \beta} \le K_i, \tag{4}$$

where $g_i(0) = 0, \alpha, \beta \in R$, $\alpha \neq \beta$ and denote $K = \max\{K_1, K_2, \cdots, K_n\}$.

Remark 1 *Under the Assumption 2 , one has*

$$x^T(t)K^2x(t) - g^T(x(t))g(x(t)) \ge 0, \quad x^T(t)Kx(t) - g^T(x(t))x(t) \ge 0 \tag{5}$$

Assumption 3 *For each $i(i = 1, 2, \cdots, n)$, time-delay function $h_i(t)$ is real valued continuous function and satisfies*

$$\sigma_i = \inf_{t\in[0,+\infty)} \{1 - \dot{h}(t)\} > 0,$$

let $\sigma = \min\{\sigma_1, \sigma_2, \cdots \sigma_n\}$.

Definition 1 *Neural network (1) with input $u(t)$ and output $y(t)$ is said be passive if there is a constant γ such that*

$$2\int_0^T u^T(s)y(s)ds \geq -\gamma \int_0^T u^T(s)u(s)ds, \tag{6}$$

for all $T \geq 0$ and for all solutions of neural network (1) with zero initial values.

Lemma 1 *For all $\varepsilon > 0$, $a \in R^n$, $b \in R^n$, the following inequality holds*

$$2a^T b \leq \varepsilon a^T a + \varepsilon^{-1} b^T b. \tag{7}$$

Lemma 2 *For any constant matrix $M > 0$, any scalars a and b with $a < b$, and a vector function $x(t) : [a, b] \to R$ such that the integrals concerned are well defined, then the following inequality holds:*

$$[\int_a^b x(s)ds]^T M[\int_a^b x(s)ds] \leq (b-a)\int_a^b x^T(s)Mx(s)ds. \tag{8}$$

3 Main results

Theorem 1 *Under Assumption 1, Assumption 3 and $\lambda_k^2 \leq 1$, neural network (1) is passive if there exist a positive definite matrix $P = (p_{ij})_{n\times n}$ and a positive scalars $\varepsilon > 0$ with $\gamma > 3\varepsilon + 2$ such that the following inequality holds:*

$$-(PA + AP) + 4\varepsilon^{-1}P^2 + \varepsilon L^2 B_0^T B_0 + \frac{\varepsilon}{\sigma} L^2 B_1^T B_1 + \varepsilon\tau^2 L^2 B_2^T B_2 + 2\varepsilon^{-1} L^2 I \leq 0. \tag{9}$$

Proof. Take $B_1^T B_1 = Q = (q_{ij})_{n\times n}$, $B_2^T B_2 = R = (r_{ij})_{n\times n}$ and consider the following Lyapunov -Krasovskii functional:

$$V(t) = V_1(t) + V_2(t), \tag{10}$$

where

$V_1(t) = x^T(t)Px(t),$

$V_2(t) = \frac{\varepsilon}{\sigma}\int_{t-h(t)}^t g^T(x(s))Qg(x(s))ds + \varepsilon\tau\int_{t-\tau}^t\int_s^t g^T(x(u))Rg(x(u))duds.$

When $t \neq t_k$, taking the derivative of (10) along the solution of system (1) yields

$$\dot{V}_1(t) = -x^T(t)(PA + AP)x(t) + 2x^T(t)P[B_0 g(x(t)) + B_1 g(x(t-h(t))) + B_2\int_{t-\tau(t)}^t g(s)ds + u(t)], \tag{11}$$

$$\begin{aligned}\dot{V}_2(t) = {} & \frac{\varepsilon}{\sigma} g^T(x(t))Qg(x(t))) - \frac{\varepsilon}{\sigma}(1-\dot{h}(t))g^T(x(t-h(t)))Qg(x(t-h(t)) + \varepsilon\tau^2 g^T(x(t))Rg(x(t)) \\ & -\varepsilon\tau\int_{t-\tau}^t g^T(x(s))Rg(x(s))ds.\end{aligned} \tag{12}$$

Applying the Lemma 1 and the Lemma 2 respectively, (11) and (12) can be estimated as

$$\begin{aligned}\dot{V}_1(t) \leq {} & -x^T(t)(PA + AP)x(t) + 4\varepsilon^{-1}x^T(t)P^2x(t) + \varepsilon g^T(x(t)B_0^T B_0 g(x(t)) \\ & + \varepsilon g^T(x(t-h(t)))B_1^T B_1 g(x(t-h(t))) + \varepsilon[\int_{t-\tau(t)}^t g(x(s))ds]^T B_2^T B_2[\int_{t-\tau(t)}^t g(x(s))ds] + \varepsilon u^T(t)u(t),\end{aligned} \tag{13}$$

$$\begin{aligned}\dot{V}_2(t) \leq {} & \frac{\varepsilon}{\sigma} g^T(x(t))Qg(x(t))) - \varepsilon g^T(x(t-h(t)))Qg(x(t-h(t)) + \varepsilon\tau^2 g^T(x(t))Rg(x(t)) \\ & -\varepsilon[\int_{t-\tau}^t g^T(x(s))ds]^T R\int_{t-\tau}^t g^T(x(s))ds].\end{aligned} \tag{14}$$

By (13) and (14), it can be seen that

$$\dot{V}(t) \leq x^T(t)[-(PA+AP)+4\varepsilon^{-1}P^2+\varepsilon L^2B_0^TB_0+\frac{\varepsilon}{\sigma}L^2B_1^TB_1+\varepsilon\tau^2L^2B_2^TB_2]x(t)+\varepsilon u^T(t)u(t). \quad (15)$$

Then, for $t \neq t_k$ we have

$$\begin{aligned} &\dot{V}(t)-2y^T(t)u(t)-\gamma u^T(t)u(t) \\ &\leq x^T(t)[-(PA+AP)+4\varepsilon^{-1}P^2+\varepsilon L^2B_0^TB_0+\frac{\varepsilon}{\sigma}L^2B_1^TB_1+\varepsilon\tau^2L^2B_2^TB_2+2\varepsilon^{-1}L^2I]x(t) \\ &\qquad +(3\varepsilon+2-\gamma)u^T(t)u(t) \\ &\leq 0. \end{aligned} \quad (16)$$

On the other hand, when $t = t_k$

$$\begin{aligned} V(t_k) &= V_1(t_k)+V_2(t_k) \\ &= \lambda_k^2x^T(t_k^-)Px(t_k^-)+\frac{\varepsilon}{\sigma}\int_{t_k^- - h(t_k^-)}^{t_k^-}g^T(x(s))Qg(x(s))ds+\varepsilon\tau\int_{t_k^- -\tau}^{t_k^-}\int_s^{t_k^-}g^T(x(u))Rg(x(u))duds. \end{aligned} \quad (17)$$

Owing to $\lambda_k^2 \leq 1$, we have

$$V(t_k) \leq V(t_k^-). \quad (18)$$

By integrating $\dot{V}(t)$ with respect to t over the time period $t_0 = 0$ to $T(t_k \leq t < t_{k+1}, k = 0,1,2,\cdots)$ and combining with (18), we can get

$$\begin{aligned} \int_0^T\dot{V}(s)ds &= \int_0^{t_1}\dot{V}(s)ds+\int_{t_1}^{t_2}\dot{V}(s)ds+\cdots+\int_{t_{k-1}}^{t_k}\dot{V}(s)ds+\int_{t_k}^T\dot{V}(s)ds \\ &= V(t_1^-)-V(t_1)+\cdots+V(t_{k-1}^-)-V(t_{k-1})+V(T)-V(0) \\ &\geq V(T)-V(0)=V(T)>0. \end{aligned} \quad (19)$$

Combining (16) and (19), we have

$$2\int_0^T y^T(s)u(s)ds \geq V(T)-V(t_0)-\gamma u^T(t)u(t). \quad (20)$$

That is ,

$$\int_0^T y^T(s)u(s)ds \geq -\frac{\gamma}{2}u^T(t)u(t), \quad (21)$$

which implies neural network (1) is passive. The proof is completed. ■

Remark 2 *Making use of Schur decomposition method, the matrix inequality (9) is equivalent to the following LMI with respect to the matrix P :*

$$\begin{pmatrix} -(PA+AP)+\varepsilon L^2B_0^TB_0+\frac{\varepsilon}{\sigma}L^2B_1^TB_1+\varepsilon\tau^2L^2B_2^TB_2+2\varepsilon^{-1}L^2I & P \\ P & -\frac{\varepsilon}{4}I \end{pmatrix} \leq 0. \quad (22)$$

Corollary 1 *Under assumptions 1 and 3, neural network (1) without impulse effects*

$$\begin{cases} \dot{x}(t) = -Ax(t)+B_0g(x(t))+B_1g(x(t-h(t)))+B_2\int_{t-\tau(t)}^t g(x(s))ds+u(t), \\ y(t) = g(x(t))+g(x(t-h(t)))+u(t), \end{cases} \quad (23)$$

is passive if there exist a positive definite matrix $P = (p_{ij})_{n\times n}$ and a positive scalars $\varepsilon > 0$ with $\gamma > 3\varepsilon + 2$ such that the following inequality holds:

$$-(PA+AP)+4\varepsilon^{-1}P^2+\varepsilon L^2B_0^TB_0+\frac{\varepsilon}{\sigma}L^2B_1^TB_1+\varepsilon\tau^2L^2B_2^TB_2+2\varepsilon^{-1}L^2I \leq 0. \quad (24)$$

Theorem 2 *Under Assumption 2, Assumption 3 and* $\lambda_k^2 \le 1$ *, neural network (1) is passive if there exist a positive definite matrix* $P = (p_{ij})_{n\times n}$ *and positive scalars* $\varepsilon > 0, \gamma > 0$ *, such that the following inequality holds:*

$$\Omega = \begin{pmatrix} -PA - AP + \varepsilon K^2 & PB_0 - A & PB_1 & PB_2 & P \\ * & 2B_0 + (1+\tau^2-\varepsilon) & B_1 & B_2 & 0 \\ * & * & -\sigma I & 0 & -I \\ * & * & * & -I & 0 \\ * & * & * & * & -(2+\gamma)I \end{pmatrix} \le 0. \quad (25)$$

Proof. Consider the following Lyapunov -Krasovskii functional:

$$V(t) = x^T(t)Px(t) + 2\sum_{i=1}^{n}\int_0^{x_i(t)} g_i(s)ds + \sum_{i=1}^{n}\int_{t-h_i(t)}^{t} g_i^2(x_i(s))ds + \tau\sum_{i=1}^{n}\int_{t-\tau}^{t}\int_s^t g_i^2(x_i(u))duds. \quad (26)$$

When $t \ne t_k$, the derivative of (26) along the solution of system (1) can be given as follows:

$$\begin{aligned} \dot V(t) \le & -x^T(t)(PA+AP)x(t) + 2x^T(t)(PB_0 - A)g(x(t)) + 2x^T(t)PB_1 g(x(t-h(t))) \\ & +2x^T(t)PB_2\int_{t-\tau(t)}^{t} g(s)ds + 2x^T(t)Pu(t) + g^T(x(t))(2B_0 + (1+\tau^2)I)g(x(t)) \\ & +2g^T(x(t))B_1 g(x(t-h(t))) + 2g^T(x(t))B_2\int_{t-\tau(t)}^{t} g(x(s))ds + 2g^T(x(t))u(t) \\ & -\sigma g^T(x(t-h(t)))g(x(t-h(t)) - [\int_{t-\tau(t)}^{t} g(s)ds]^T[\int_{t-\tau(t)}^{t} g(s)ds]. \end{aligned} \quad (27)$$

Combining with (5), we have

$$\begin{aligned} & \dot V(t) - 2y^T(t)u(t) - \gamma u^T(t)u(t) \\ & \le \eta^T(t)\Omega\eta(t) \\ & \le 0, \end{aligned} \quad (28)$$

where $\eta(t) = (x^T(t), g^T(x(t)), g^T(x(t-h(t))), (\int_{t-\tau(t)}^{t} g(s)ds)^T, u^T(t))^T$.

On the other hand, when $t = t_k$

$$\begin{aligned} V(t_k) = \lambda_k^2 x^T(t_k^-)Px(t_k^-) + 2\sum_{i=1}^{n}\int_0^{\lambda_k x_i(t_k^-)} g_i(s)ds + \sum_{i=1}^{n}\int_{t_k^- - h_i(t)}^{t_k^-} g_i^2(x_i(s))ds \\ +\tau\sum_{i=1}^{n}\int_{t_k^- - \tau}^{t_k^-}\int_s^{t_k^-} g_i^2(x_i(u))duds. \end{aligned} \quad (29)$$

Owing to $\lambda_k^2 \le 1$, we have

$$V(t_k) \le V(t_k^-). \quad (30)$$

By integrating $\dot V(t)$ with respect to t over the time period $t_0 = 0$ to $T(t_k \le t < t_{k+1}, k = 0, 1, 2, \cdots)$ and combining with (30) and employing the similar process of (19), we can get

$$\int_0^T \dot V(s)ds \ge V(T) - V(0) = V(T) > 0. \quad (31)$$

Combining (28) and (31), we have

$$2\int_0^T y^T(s)u(s)ds \ge V(T) - V(t_0) - \gamma u^T(t)u(t). \quad (32)$$

That is ,

$$\int_0^T y^T(s)u(s)ds \ge -\frac{\gamma}{2}u^T(t)u(t), \quad (33)$$

which implies neural network (1) is passive. The proof is completed.

■

Corollary 2 *Under Assumption 2, Assumption 3 and $\lambda_k^2 \le 1$, neural network (23) is passive if there exist a positive definite matrix $P = (p_{ij})_{n\times n}$ and positive scalars $\varepsilon > 0, \gamma > 0$, such that the following inequality holds:*

$$\Omega = \begin{pmatrix} -PA - AP + \varepsilon K^2 & PB_0 - A & PB_1 & PB_2 & P \\ * & 2B_0 + (1+\tau^2 - \varepsilon) & B_1 & B_2 & 0 \\ * & * & -\sigma I & 0 & -I \\ * & * & * & -I & 0 \\ * & * & * & * & -(2+\gamma)I \end{pmatrix} \le 0. \tag{34}$$

4 Examples

In this section, numerical examples are given to verify the validity of the theoretical result.

Example 1 *Consider the following impulsive neural networks:*

$$\begin{cases} \dot{x}_1(t) = -1.8x_1(t) + 0.2g_1(x_1(t)) - 0.1g_2(x_2(t)) - 0.2g_1(x_1(t-h_1(t)) + 0.1g_2(x_2(t-h_2(t)) \\ \qquad +0.1\int_{t-\tau_1(t)}^{t} g_1(x_1(s))ds - 0.1\int_{t-\tau_2(t)}^{t} g_2(x_2(s))ds + \frac{1}{2}\sin t, \quad t \ne t_k, \\ \dot{x}_2(t) = -1.8x_1(t) - 0.1g_1(x_1(t)) - 0.3g_2(x_2(t)) - 0.1g_2(x_2(t-h_2(t)) \\ \qquad -0.1\int_{t-\tau_1(t)}^{t} g_1(x_1(s))ds - 0.1\int_{t-\tau_2(t)}^{t} g_2(x_2(s))ds + \cos t, \quad t \ne t_k, \\ x_1(t_k) = -0.64x_1(t_k^-), \quad k \in N, \\ x_2(t_k) = 0.36x_2(t_k^-), \quad k \in N. \end{cases} \tag{35}$$

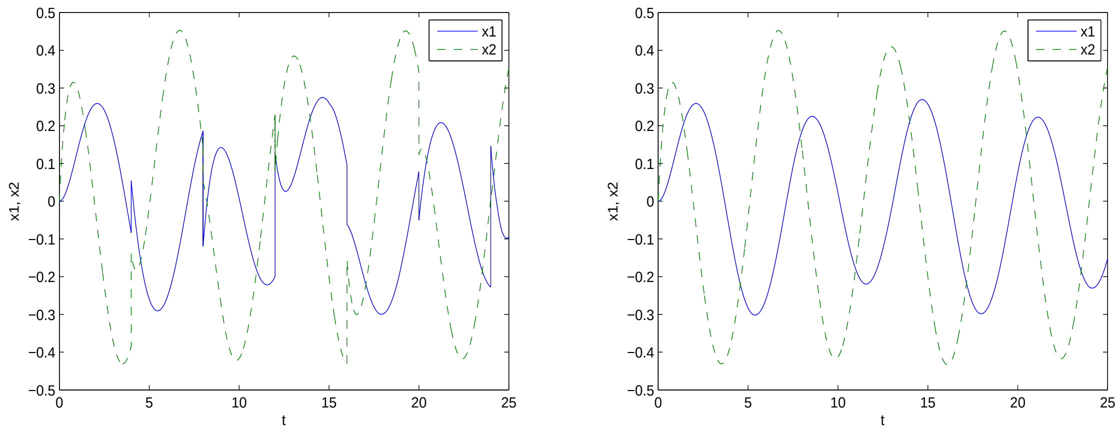
where $g_i(x_i(t)) = (|x_i(t)+1| - |x_i(t)-1|)/2, i = 1,2, h(t) = \frac{1}{2}t - \frac{1}{2}\sin\frac{t}{2}, \tau(t) = \cos^2 t, t_k = 4k.$

We can calculate that $\sigma = \inf_{t\in[0,+\infty)}\{1 - \dot{h}(t)\} = \frac{1}{4} > 0, \tau = 1.$

By taking $P = diag(1,1), \varepsilon = 3.0363$ *, we have*

$$-(PA + AP) + 4\varepsilon^{-1}P^2 + \varepsilon L^2 B_0^T B_0 + \frac{\varepsilon}{\sigma}L^2 B_1^T B_1 + \varepsilon\tau^2 L^2 B_2^T B_2 + 2\varepsilon^{-1}L^2 I \le 0.$$

We can find that it satisfies (9), according to Theorem 1, the passivity of neural network (35) can be achieved.



(a) The state curves with impulsive effects

(b) The state curves without impulsive effects

Figure 1: The state curves of neural network (35)

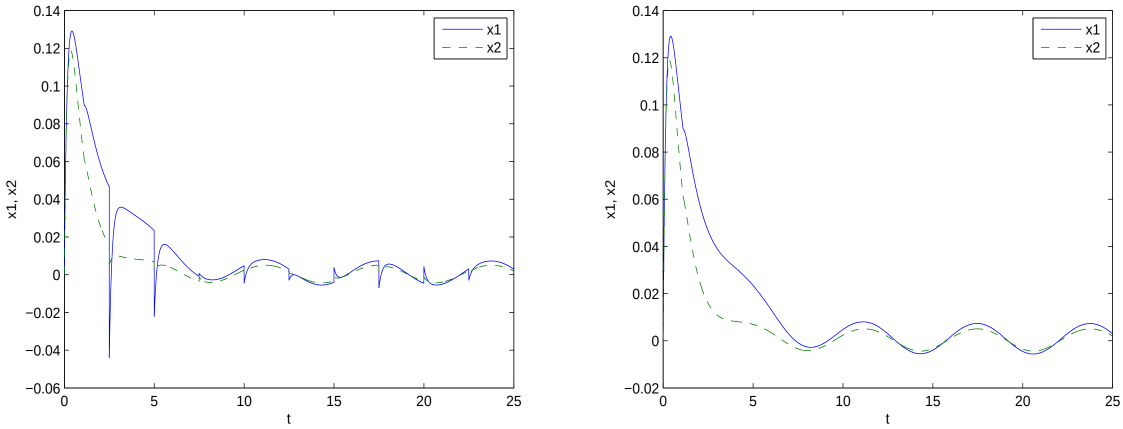
Example 2 *Consider the following two-neuron networks:*

$$\begin{cases} \dot{x}_1(t) = -3.6x_1(t) - g_1(x_1(t)) + 0.2g_2(x_2(t)) + 0.5g_1(x_1(t-h_1(t)) + 0.3g_2(x_2(t-h_2(t)) \\ \quad -\int_{t-\tau_1(t)}^{t} g_1(x_1(s))ds + 0.3\int_{t-\tau_2(t)}^{t} g_2(x_2(s))ds + e^{-\frac{1}{2}t}, \quad t \neq t_k, \\ \dot{x}_2(t) = -3.6x_1(t) - g_2(x_2(t)) + 0.2g_1(x_1(t-h_1(t)) + 0.4g_2(x_2(t-h_2(t)) \\ \quad +0.1\int_{t-\tau_1(t)}^{t} g_1(x_1(s))ds - 0.6\int_{t-\tau_2(t)}^{t} g_2(x_2(s))ds + e^{-t}, \quad t \neq t_k, \\ x_1(t_k) = -0.94x_1(t_k^-), \quad k \in N, \\ x_2(t_k) = 0.35x_2(t_k^-), \quad k \in N. \end{cases} \tag{36}$$

where $g_i(x_i(t)) = \tanh(x_i(t)), h_i(t) = 1 + \frac{1}{3}e^{-t}, \tau_i(t) = 0.75 + 0.25\sin t, i = 1, 2, t_k = 2.5k.$

We can calculate that $\sigma = \inf_{t\in[0,+\infty)}\{1 - \dot{h}(t)\} = 1 > 0$, $\tau = 1$. *For given* $\gamma = 1$, *by using the* $MATLABLMI$ *toolbox, we can compute the following feasible solution for* LMI *(25):* $\varepsilon = 4.9009$, $P = \begin{pmatrix} 2.1555 & 0.1285 \\ 0.1285 & 2.7438 \end{pmatrix}$.

According to Theorem 2, the passivity of neural network (36) can be achieved.



(a) The state curves with impulsive effects

(b) The state curves without impulsive effects

Figure 2: The state curves of neural network (36)

5 Conclusions

In this paper, the problem of delay-dependent passivity for impulsive cellular neural networks with mixed time-varying delays has been investigated. Applying Lyapunov-Krasovskii functional and matrix inequality approach, some new sufficient conditions of the passivity have been obtained. At last, some numerical examples have been given to show the effectiveness of the proposed result.

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