SCIENCE CHINA
Information Sciences

• RESEARCH PAPER •

May 2020, Vol. 63 150206:1–150206:12
https://doi.org/10.1007/s11432-019-2694-y

Special Focus on Advanced Techniques for Event-Triggered Control and Estimation

Event-triggered hybrid impulsive control for synchronization of memristive neural networks

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Received 15 June 2019/Accepted 16 September 2019/Published online 27 March 2020

Abstract This paper is concerned with the complete synchronization of memristive neural networks (MNNs) with time-varying delays. An event-triggered hybrid state feedback and impulsive controller is designed to save the limited system communication resources, and parameter mismatch is considered in the control design process. Based on the Lyapunov functional approach and the comparison principle for impulsive systems, a sufficient synchronization criterion is developed to derive the master MNN and response MNN. Additionally, under the event-triggered mechanism there exists a positive lower bound for inter-execution time, which implies the avoidance of Zeno behavior. Finally, a numerical example is provided to demonstrate the effectiveness of the proposed synchronization design methods.

Keywords event-triggered, synchronization, memristive neural networks, impulsive control, Zeno behavior

Citation Zhang Y J, Bao Y G. Event-triggered hybrid impulsive control for synchronization of memristive neural networks. Sci China Inf Sci, 2020, 63(5): 150206, https://doi.org/10.1007/s11432-019-2694-y

1 Introduction

In 1971, based on physical symmetry arguments, Chua [1] proposed a new two-terminal circuit element named as a memristor. A physical model of the memristor was first presented by Strukov et al. [2] in 2008. One of the distinctive properties of the memristor is that its value, i.e., memristance, relates to the quantity of charge passing through it. This property enables memristor device to possess a memory function [3]. In biological neural networks, synapses among the neurons have the characteristic of long-term memory. Typically, the connection weights of existing artificial neural networks are realized by resistors that cannot implement a memory function. For better understanding of the working behavior of the human brain, a new type of artificial neural network, namely, a memristive neural network (MNN) has been constructed. On the other hand, time delays exist inevitably in artificial neural networks. In recent years, considerable attention has been paid to the stability of delayed neural networks (see [4–6] and the references therein).

Synchronization of neural networks has attracted the attention of scholars from different fields owing to its various applications from signal processing to secure communication. Significant effort has been directed to investigate the synchronization of neural networks and various control methods such as state or output feedback control [7,8], intermittent control [9], adaptive control [10], and impulsive control [11,12] have been proposed. Among the aforementioned control methods, the impulsive control strategy seems the most effective strategy to deal with systems that cannot endure continuous control input such as the saving rate regulation of a bank [13]. Besides, it only requires small control gains and acts at certain

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discrete instants, thereby reducing the amount of transmitted information and control costs [14]. Considering the advantages of the impulsive control strategy, the issue of impulsive synchronization of MNNs has been wildly studied [15–19]. In [15], by utilizing the distributed impulsive control method, the synchronization problem for a class of MNNs with stochastic disturbance has been extensively studied. Hybrid impulsive and state feedback controllers [16] have been designed to ensure the dynamics of a response MNN synchronized with the master. Under parameter mismatch conditions, the quasi-synchronization problem of heterogeneous dynamic networks via distributed impulsive control has been well studied [13].

Recently, the event-triggered control (ETC) strategy has received significant research attention owing to its superior performance in saving computation resources and network bandwidth [20–22]. The main idea of the ETC strategy is that the triggering instants only occur if a certain predefined condition is violated. In [23], the event-triggered scheduler is utilized to relax the execution requirements while guaranteeing the desired performance compared with the time-triggered approach. In [24], the self-triggered control strategy is used to determine the next triggering instant, and the stability of a closed-loop system is also discussed. A type of discrete event-triggered controller has been proposed in [25], and ETC systems have been modeled as time-delayed systems. Since then, the ETC strategy has been extensively applied to research for synchronization [26–30] and state estimation [31–33]. A dynamic ETC approach [29] has been adopted to study the synchronization of discrete complex dynamical networks with time delays. A hybrid triggered scheme has been proposed in [32], and state estimation of neural networks under quantization effect and cyber-attacks has been well studied.

Considering the advantages of the impulsive control method and the ETC strategy, we combine the two strategies and propose the event-triggered impulsive control (ETIC) method. The main idea of the ETIC method is that the impulsive time sequences are the same as the event-triggering instants, which are determined by specific triggered conditions. Compared to the traditional impulsive control method [22,34,35], the ETIC strategy can reduce the communication burden and save the communication resources. In addition, the ETIC strategy has been applied to improve the performance of differential evolution [36]. However, few studies have investigated the ETIC method [37–39]. In [37], the distributed ETIC strategy is proposed, and the leader-following consensus of multi-agent systems is discussed. Based on the event-based impulsive control method, the problem for the stabilization of continuous-time systems has been studied in [38]. Quasi-synchronization of delayed MNNs under event-triggered and self-triggered impulsive control methods has been studied [39]. The connection weights of MNNs depend on the system states; therefore, the weight matrices may differ given different initial conditions. In other words, it is not reasonable to assume that different MNNs have the same initial conditions. Thus, parameter mismatch will occur between different MNNs. MNNs synchronization can be considered as the synchronization of a class of heterogenous systems. Existing ETIC methods [37–39] can only guarantee the quasi-synchronization of MNNs. Therefore, an event-triggered hybrid state feedback and impulsive controller is required to ensure the complete synchronization of MNNs.

This paper primarily focuses on complete synchronization of MNNs via event-triggered hybrid state feedback and impulsive control. The primarily contributions of this study can be summarized as follows. (1) Previously proposed ETIC methods [37–39] cannot be used to achieve complete synchronization of MNNs. To solve the problem, a new type of event-triggered hybrid state feedback and impulsive control method is proposed. (2) Compared to a previously proposed state feedback controller [30] that can achieve complete synchronization of MNNs, the proposed controller is theoretically more logical and easier to implement in practice. (3) Based on the Lyapunov functional method and the comparison principle for impulsive systems, we derive a sufficient criterion to guarantee the complete synchronization of MNNs. In addition, the Zeno behavior is excluded.

The remainder of this paper is organized as follows. In Section 2, some assumptions, definitions, and lemmas are presented. In addition, the design of the event-triggered hybrid impulsive controller is described. In Section 3, some sufficient criteria to ensure the exponential synchronization are derived by using Lyapunov method. In Section 4, a numerical example is provided to demonstrate the accuracy of the derived results. Conclusion and suggestions for future work are presented in Section 5.

Notations. $\mathbb{R}$ denotes the set of all real numbers. $\mathbb{R}^n$ denotes n-dimension Euclidean space. $\mathbb{N} =$

$\{0,1,2,3,\ldots\}$. For vector $x=(x_1,x_2,\ldots,x_n)^{\mathrm T}$ or a real matrix $A=(a_{rm})_{n\times n}$, $|x|=(|x_1|,|x_2|,\ldots,|x_n|)^{\mathrm T}$, $|A|=(|a_{rm}|)_{n\times n}$, $\|x\|_1=\sum_{r=1}^{n}|x_r|$ and $\|A\|_1=\max_{1\leqslant m\leqslant n}\sum_{r=1}^{n}|a_{rm}|$. For a real symmetric matrix P, $P\geqslant 0$ ($P>0$) indicates that matrix P is positive semi-definite (positive definite). The function $\mathrm{sign}(\cdot)$ is a signum function. Matrix I represents the identity matrix. Let $\tau>0$, and $\mathcal{C}([-\tau,\ 0];\mathbb{R}^n)$ denotes the set of all continuous functions from $[-\tau,\ 0]$ to $\mathbb{R}^n$.

2 Problem formulations

Consider the following MNN with time-varying delays for $r=1,2,\ldots,n$:

$$\dot{x}_r(t)=-c_rx_r(t)+\sum_{m=1}^{n}a_{rm}(x_r(t))f_r(x_r(t))+\sum_{m=1}^{n}b_{rm}(x_r(t))f_r(x_r(t-\tau_r(t))),\tag{1}$$

where $x_r(t)$ denotes the state of the rth neuron, $c_r>0$ is the self-inhibition of the rth neuron, $\tau_r(t)$ is the time-varying delay satisfying $0<\tau_r(t)<\tau$ with τ is a positive constant, $f_r(\cdot)$ is the neuron activation function, and $a_{rm}(x_r(t))$ and $b_{rm}(x_r(t))$ are the memristive and delayed memristive connection weights, respectively. Here, the memristive connection weights satisfy the following conditions:

$$a_{rm}(x_r(t))=\begin{cases}\hat{a}_{rm}, & |x_r(t)|\leqslant T_r,\\ \check{a}_{rm}, & |x_r(t)|>T_r,\end{cases}$$

$$b_{rm}(x_r(t))=\begin{cases}\hat{b}_{rm}, & |x_r(t)|\leqslant T_r,\\ \check{b}_{rm}, & |x_r(t)|>T_r,\end{cases}$$

where $T_r>0$, $\hat{a}_{rm}$, $\check{a}_{rm}$, $\hat{b}_{rm}$ and $\check{b}_{rm}$ are given constants. The initial condition of system (1) is defined as $x_r(t)=\psi_r(t)$, $t\in[-\tau,\ 0]$, where $\psi_r(t)\in\mathcal{C}([-\tau,\ 0];\mathbb{R})$.

Definition 1 ([40])**.** For the system $\frac{\mathrm{d}x}{\mathrm{d}t}=f(x)$, $x\in\mathbb{R}^n$, with discontinuous right-hand sides, a set-valued map is defined as

$$\psi(x)=\cap_{\delta>0}\cap_{\mu(N)=0}\overline{\mathrm{co}}[f(B(x,\delta))\backslash N],$$

where $\overline{\mathrm{co}}[E]$ is the closure of the convex hull of set E, $B(x,\delta)=\{y:\|y-x\|\leqslant\delta\}$, and $\mu(N)$ is the Lebesgue measure of set N. A solution in Filippov's sense of the Cauchy problem for this system with initial condition $x(0)=x_0$ is an absolutely continuous function $x(t)$, $t\in[0,T]$, that satisfies $x(0)=x_0$ and differential inclusion: $\frac{\mathrm{d}x}{\mathrm{d}t}\in\psi(x)$, for a.e. $t\in[0,T]$.

According to Definition 1, it follows from system (1) that

$$\dot{x}_r(t)\in-c_rx_r(t)+\sum_{m=1}^{n}\mathrm{co}[a_{rm}(x_r(t))]f_r(x_r(t))+\sum_{m=1}^{n}\mathrm{co}[b_{rm}(x_r(t))]f_r(x_r(t-\tau_r(t))).\tag{2}$$

Equivalently, there exist measurable functions $\bar{a}_{rm}(t)\in\mathrm{co}[a_{rm}(x_r(t))]$ and $\bar{b}_{rm}(t)\in\mathrm{co}[b_{rm}(x_r(t))]$ such that

$$\dot{x}_r(t)=-c_rx_r(t)+\sum_{m=1}^{n}\bar{a}_{rm}(t)f_r(x_r(t))+\sum_{m=1}^{n}\bar{b}_{rm}(t)f_r(x_r(t-\tau_r(t))).\tag{3}$$

Here, let system (1) be the master system. The response system is described as

$$\dot{y}_r(t)=-c_ry_r(t)+\sum_{m=1}^{n}a_{rm}(y_r(t))f_r(y_r(t))+\sum_{m=1}^{n}b_{rm}(y_r(t))f_r(y_r(t-\tau_r(t)))+u_r(t),\tag{4}$$

where $y_r(t)$ denotes the state of the rth neuron and $u_r(t)$ is the control to be designed. The initial condition is defined as $y_r(t)=\tilde{\psi}_r(t)$, $t\in[-\tau,\ 0]$, where $\tilde{\psi}_r(t)\in\mathcal{C}([-\tau,\ 0];\mathbb{R})$.

Similar to the above discussion, there exist measurable functions $\grave{a}_{rm}(t) \in \mathrm{co}[a_{rm}(y_r(t))]$ and $\grave{b}_{rm}(t) \in \mathrm{co}[b_{rm}(y_r(t))]$ such that

$$\dot{y}_r(t) = -c_r y_r(t) + \sum_{m=1}^{n} \grave{a}_{rm}(t) f_r(y_r(t)) + \sum_{m=1}^{n} \grave{b}_{rm}(t) f_r(y_r(t-\tau_r(t))) + u_r(t). \tag{5}$$

By defining synchronization error $\epsilon_r(t) = y_r(t) - x_r(t)$, the error system is written as

$$\begin{aligned} \dot{\epsilon}_i(t) = & -c_r \epsilon_r(t) + \sum_{m=1}^{n} [\grave{a}_{rm}(t) f_r(y_r(t)) - \bar{a}_{rm}(t) f_r(x_r(t))] \\ & + \sum_{m=1}^{n} [\grave{b}_{rm}(t) f_r(y_r(t-\tau_r(t))) - \bar{b}_{rm}(t) f_r(x_r(t-\tau_r(t)))] + u_r(t). \end{aligned} \tag{6}$$

The event-triggered hybrid state feedback and impulsive controller $u_r(t)$ is designed as

$$u_r(t) = -k_1 \epsilon_r(t_k) - k_2 \,\mathrm{sign}(\epsilon_r(t_k)) + \sum_{k=0}^{+\infty} d_k \epsilon_r(t) \delta(t - t_{k+1}^-), \quad t \in [t_k, t_{k+1}), \quad k \in \mathbb{N}, \tag{7}$$

where d_k is the impulsive control gain, $d_k \neq 0$, $k_1 > 0$ and $k_2 > 0$ are the state feedback control gains, time sequence $\{t_k\}$ denotes the event-triggering instants satisfying $0 = t_0 < t_1 < t_2 < \cdots < t_k < \cdots$, and $\delta(\cdot)$ is the Dirac delta function.

By substituting the controller $u_r(t)$ into the error system (6), integrating both sides from $t_{k+1} - h$ to $t_{k+1} + h$, and letting $h \to 0^+$, we obtain

$$\epsilon_r(t_{k+1}^+) - \epsilon_r(t_{k+1}^-) = \lim_{h \to 0^+} \int_{t_{k+1}-h}^{t_{k+1}+h} \sum_{k=0}^{+\infty} d_k \epsilon_r(t) \delta(t - t_{k+1}^-) \mathrm{d}t = d_{k+1} \epsilon_r(t_{k+1}^-),$$

where $\epsilon_r(t_{k+1}^+) = \lim_{h \to 0^+} \epsilon_r(t_{k+1} + h)$ and $\epsilon_r(t_{k+1}^-) = \lim_{h \to 0^+} \epsilon_r(t_{k+1} - h)$. Without loss of generality, we assume $\epsilon_r(t_{k+1}^+) = \epsilon_r(t_{k+1})$, which implies that $\epsilon_r(t)$ is continuous from the right side.

The system (6) with controller $u_r(t)$ is rewritten as

$$\begin{cases} \dot{\epsilon}_r(t) = -c_r \epsilon_r(t) + \displaystyle\sum_{m=1}^{n} [\grave{a}_{rm}(t) f_r(y_r(t)) - \bar{a}_{rm}(t) f_r(x_r(t))] \\ \qquad\quad + \displaystyle\sum_{m=1}^{n} [\grave{b}_{rm}(t) f_r(y_r(t-\tau_r(t))) - \bar{b}_{rm}(t) f_r(x_r(t-\tau_r(t)))] \\ \qquad\quad - k_1 \epsilon_r(t_k) - k_2 \,\mathrm{sign}(\epsilon_r(t_k)), \quad t \in [t_k,\ t_{k+1}), \\ \epsilon_r(t_{k+1}) = (1 + d_{k+1}) \epsilon_r(t_{k+1}^-). \end{cases} \tag{8}$$

By rearrange (8) into matrix form, we obtain

$$\begin{cases} \dot{\epsilon}(t) = -C\epsilon(t) + A_2(t) f(y(t)) - A_1(t) f(x(t)) + B_2(t) f(y(t-\tau(t))) - B_1(t) f(x(t-\tau(t))) \\ \qquad\quad - k_1 \epsilon(t_k) - k_2 \,\mathrm{sign}(\epsilon(t_k)), \quad t \in [t_k,\ t_{k+1}), \\ \epsilon(t_{k+1}) = (1 + d_{k+1}) \epsilon(t_{k+1}^-), \end{cases} \tag{9}$$

where $\epsilon(t) = (\epsilon_1(t), \epsilon_2(t), \ldots, \epsilon_n(t))^{\mathrm{T}}$, $A_1(t) = [\bar{a}_{rm}(t)]_{n \times n}$, $A_2(t) = [\grave{a}_{rm}(t)]_{n \times n}$, $B_1(t) = [\bar{b}_{rm}(t)]_{n \times n}$, $B_2(t) = [\grave{b}_{rm}(t)]_{n \times n}$, $f(x(t)) = (f_1(x_1(t)), f_2(x_2(t)), \ldots, f_n(x_n(t)))^{\mathrm{T}}$, $f(y(t)) = (f_1(y_1(t)), f_2(y_2(t)), \ldots, f_n(y_n(t)))^{\mathrm{T}}$, and $\mathrm{sign}(\epsilon(t_k)) = (\mathrm{sign}(\epsilon_1(t_k)), \mathrm{sign}(\epsilon_2(t_k)), \ldots, \mathrm{sign}(\epsilon_n(t_k)))^{\mathrm{T}}$. The initial condition is $\epsilon(t) = \phi(t) = \psi(t) - \tilde{\psi}(t)$, $t \in [-\tau,\ 0]$, with $\psi(t) = (\psi_1(t),\ \psi_2(t), \ldots, \psi_n(t))$ and $\tilde{\psi}(t) = (\tilde{\psi}_1(t), \tilde{\psi}_2(t), \ldots, \tilde{\psi}_n(t))$.

Remark 1. Note that the mathematical model description provided here is similar to common impulsive systems. However, differing from impulsive time sequences, which are periodic in [15–19], the impulsive time sequences herein are event-triggering instants determined by the predefined event-triggered condition. Therefore, the communication burden can be reduced, and limited communication resources can be utilized effectively.

Throughout this paper, we define $\tilde{a}_{rm} = \max\{|\hat{a}_{rm}|, |\check{a}_{rm}|\}$, $\tilde{b}_{rm} = \max\{|\hat{b}_{rm}|, |\check{b}_{rm}|\}$, $\tilde{A} = [\tilde{a}_{rm}]_{n\times n}$ and $\tilde{B} = [\tilde{b}_{rm}]_{n\times n}$.

We define $E(t) = k_1\epsilon(t_k) + k_2\,\mathrm{sign}(\epsilon(t_k)) - k_1\epsilon(t) - k_2\,\mathrm{sign}(\epsilon(t)), t \in [t_k, t_{k+1})$, where $\epsilon(t)$ is the current error state and $\epsilon(t_k)$ represents the last transmitted error state. The event-triggered condition is designed as

$$t_{k+1} = \{t > t_k | \|E(t)\|_1 \geqslant \sigma k_1 \|\epsilon(t)\|_1 + n\sigma k_2\}, \tag{10}$$

where $\sigma \in (0, 1)$ is a constant to be designed.

The following definitions, assumption, and lemma are required to derive the main result.

Definition 2 ([41])**.** For $(t, x(t)) \in [t_{k-1}, t_k) \times \mathbb{R}^n$, we define

$$D^+V(t, x(t)) = \lim_{h\to 0^+} \frac{1}{h}\{V(t+h, x(t+h)) - V(t, x(t))\}.$$

Definition 3. The trivial solution of error system (9) is considered globally exponentially stable; in other words, Eqs. (1) and (4) are synchronized exponentially, if there exist positive constants $M \geqslant 1$, $\lambda > 0$ such that

$$\|\epsilon(t)\|_1 \leqslant M\|\phi(s)\|_\tau \mathrm{e}^{-\lambda(t-t_0)}, \quad t \geqslant t_0,$$

where $\|\phi(s)\|_\tau = \|\psi(s) - \tilde{\psi}(s)\|_\tau = \sup_{t_0-\tau\leqslant s\leqslant t_0} \|\psi(s) - \tilde{\psi}(s)\|_1$.

Assumption 1. Assume that the neuron activation function $f_r(\cdot)$ is continuous and bounded, i.e., $|f_r(\cdot)| \leqslant M_r$, and that there exist constants l_r such that

$$|f_r(s_1) - f_r(s_2)| \leqslant l_r|s_1 - s_2|,$$

where $r = 1, 2, \ldots, n$ and $s_1, s_2 \in \mathbb{R}$.

Lemma 1 ([42])**.** Let $0 \leqslant \tau(t), \tau_1(t), \tau_2(t), \ldots, \tau_m(t) \leqslant \tilde{\tau}$,

$$F(t, u, \overline{u}_1, \cdots \overline{u}_m) : \mathbb{R}^+ \times \overbrace{\mathbb{R} \times \cdots \mathbb{R}}^{m+1} \to \mathbb{R}$$

be nondecreasing in $\overline{u}_i$ for each fixed $(t, u, \overline{u}_1, \ldots, \overline{u}_{i-1}, \overline{u}_{i+1}, \overline{u}_m), i = 1, 2, \ldots m$ and $I_k(u) : \mathbb{R} \to \mathbb{R}$ be nondecreasing in u. Assume that $u(t)$, $v(t)$ satisfy

$$\begin{cases} D^+u(t) \leqslant F(t, u(t), u(t-\tau_1), \ldots, u(t-\tau_m(t))), & t \geqslant 0, \\ u(t_k^+) \leqslant I_k(u(t_k)), & k \in \mathbb{N}, \end{cases}$$

$$\begin{cases} D^+v(t) > F(t, v(t), v(t-\tau_1), \ldots, v(t-\tau_m(t))), & t \geqslant 0, \\ v(t_k^+) \geqslant I_k(v(t_k)), & k \in \mathbb{N}. \end{cases}$$

Then $u(t) \leqslant v(t)$, for $-\tilde{\tau} \leqslant t \leqslant 0$, implies that $u(t) \leqslant v(t)$, for $t \geqslant 0$.

The primary goal of this paper is to design a hybrid impulsive controller to achieve complete synchronization between the master MNN (1) and response MNN (4).

3 Main results

Here, we provide a sufficient criterion to guarantee that error system (9) is globally stable such that synchronization of systems (1) and (4) can be realized.

Theorem 1. Under Assumption 1 and the event-triggered mechanism (10), error system (9) is globally exponentially stable, if the following conditions are satisfied:

$$\sum_{r=1}^{n} \varpi_r \leqslant (1 - n\sigma)k_2, \tag{11}$$

and

$$\alpha + \frac{\ln\mu}{\rho} + \frac{\beta}{\mu} < 0, \tag{12}$$

where $\alpha = -c_{\min} - k_1 + l_{\max}\|\tilde{A}\|_1 + \sigma k_1$, $\beta = l_{\max}\|\tilde{B}\|_1$, $\mu = \max_{k\in\mathbb{N}}\{|1+d_k|\} \in (0,1)$, $c_{\min} = \min\{c_r, r=1,2,\ldots,n\}$, $l_{\max} = \min\{l_r, r=1,2,\ldots,n\}$, $\varpi_r = \sum_{m=1}^{n}(|\hat{a}_{rm} - \check{a}_{rm}| + |\hat{b}_{rm} - \check{b}_{rm}|)M_m$, $\rho = \max_{k\in\mathbb{N}}\{t_{k+1} - t_k\}$, and $\lambda > 0$ is a solution of $\beta \mathrm{e}^{\lambda\tau} + (\alpha + \frac{\ln\mu}{\rho} + \lambda)\mu = 0$.

Proof. We construct the following Lyapunov function:

$$V(t) = \|\epsilon(t)\|_1.$$

When $t \in [t_k, t_{k+1})$, by taking the derivative of $V(t)$ along system (9), we obtain

$$\begin{aligned} D^+V(t) &= \mathrm{sign}^{\mathrm{T}}(\epsilon(t))[-C\epsilon(t) + A_2(t)f(y(t)) - A_1(t)f(x(t)) + B_2(t)f(y(t-\tau(t))) \\ &\quad -B_1(t)f(x(t-\tau(t))) - E(t) - k_1\epsilon(t) - k_2\,\mathrm{sign}(\epsilon(t))] \\ &\leqslant -(c_{\min} + k_1)\|\epsilon(t)\|_1 + \mathrm{sign}^{\mathrm{T}}(\epsilon(t))[A_2(t)(f(y(t)) - f(x(t))) \\ &\quad +B_2(t)(f(y(t-\tau(t))) - f(x(t-\tau(t)))) + (A_2(t) - A_1(t))f(x(t)) \\ &\quad +(B_2(t) - B_1(t))f(y(t-\tau(t))) - E(t) - k_2\,\mathrm{sign}(\epsilon(t))]. \end{aligned} \tag{13}$$

Then, it is easy to obtain

$$\mathrm{sign}^{\mathrm{T}}(\epsilon(t))A_2(t)(f(y(t)) - f(x(t))) \leqslant l_{\max}\|\tilde{A}\|_1\|\epsilon(t)\|_1, \tag{14}$$

and

$$\mathrm{sign}^{\mathrm{T}}(\epsilon(t))B_2(t)(f(y(t-\tau(t))) - f(x(t-\tau(t)))) \leqslant l_{\max}\|\tilde{B}\|_1\|\epsilon(t-\tau(t))\|_1. \tag{15}$$

According to Assumption 1, we have

$$\begin{aligned} &\mathrm{sign}^{\mathrm{T}}(\epsilon(t))[(A_2(t) - A_1(t))f(x(t)) + (B_2(t) - B_1(t))f(y(t-\tau(t)))] \\ &\leqslant \sum_{r=1}^{n}\sum_{m=1}^{n}(|\hat{a}_{rm} - \check{a}_{rm}| + |\hat{b}_{rm} - \check{b}_{rm}|)M_m = \sum_{r=1}^{n}\varpi_r. \end{aligned} \tag{16}$$

Under the event-triggered mechanism (10), for $t \in [t_k, t_{k+1})$, we obtain

$$-\,\mathrm{sign}^{\mathrm{T}}(\epsilon(t))E(t) \leqslant \|E(t)\|_1 < \sigma k_1\|\epsilon(t)\|_1 + n\sigma k_2. \tag{17}$$

Considering (13)–(17), we obtain

$$\begin{aligned} D^+V(t) &\leqslant (-c_{\min} - k_1 + l_{\max}\|\tilde{A}\|_1 + \sigma k_1)\|\epsilon(t)\|_1 + l_{\max}\|\tilde{B}\|_1\|\epsilon(t-\tau(t))\|_1 \\ &= \alpha V(t) + \beta V(t-\tau(t)). \end{aligned} \tag{18}$$

When $t = t_{k+1}$,

$$V(t_{k+1}) = \|\epsilon(t_{k+1})\|_1 = |1+d_{k+1}|\|\epsilon(t_{k+1}^-)\|_1 \leqslant \mu V(t_{k+1}^-). \tag{19}$$

For any $\varepsilon > 0$, let $\nu(t)$ be a unique solution of impulsive delay system:

$$\begin{cases} \dot{\nu}(t) = \alpha\nu(t) + \beta\nu(t-\tau(t)) + \varepsilon, & t \neq t_k, \\ \nu(t_k^+) = \mu\nu(t_k^-), & t = t_k, \\ \nu(t) = \|\phi(t)\|_\tau, & -\tau \leqslant t \leqslant 0. \end{cases} \tag{20}$$

According to Lemma 1, $V(t) \leqslant \nu(t)$; thus, for $-\tau \leqslant t \leqslant 0$, there exists

$$0 \leqslant V(t) \leqslant \nu(t), \quad t \geqslant 0.$$

According to formula for the variation of parameters, we obtain

$$\nu(t) = W(t,0)\nu(0) + \int_0^t W(t,s) \times [\beta\nu(s-\tau(s)) + \varepsilon]\mathrm{d}s,$$

where $W(t,s)$ $(t \geqslant 0, s \geqslant 0)$ is the Cauchy matrix of linear system:

$$\begin{cases} \dot{\omega}(t) = \alpha\omega(t), & t \neq t_k, \\ \omega(t_k^+) = \mu\omega(t_k^-), & t = t_k. \end{cases}$$

According to the representation of the Cauchy matrix, we obtain

$$W(t,s) = \mathrm{e}^{\alpha(t-s)} \prod_{s<t_k\leqslant t} \mu \leqslant \mathrm{e}^{\alpha(t-s)} \mu^{\frac{t-s}{\rho}-1} = \frac{1}{\mu}\mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})(t-s)}, \quad t \geqslant s \geqslant 0. \tag{21}$$

Therefore,

$$\begin{aligned} \nu(t) &\leqslant \frac{1}{\mu}\mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})t}\|\phi(0)\|_1 + \int_0^t \frac{1}{\mu}\mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})(t-s)}[\beta\nu(s-\tau(s)) + \varepsilon]\mathrm{d}s \\ &\leqslant \gamma\mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})t} + \int_0^t \mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})(t-s)} \left[\frac{\beta}{\mu}\nu(s-\tau(s)) + \frac{\varepsilon}{\mu}\right]\mathrm{d}s, \end{aligned} \tag{22}$$

where $\gamma = \frac{1}{\mu}\|\phi(t)\|_\tau$.

Let $\eta(t) = \beta\mathrm{e}^{\lambda\tau} + (\alpha + \frac{\ln\mu}{\rho} + \lambda)\mu$. Because $\eta(0) = \beta + (\alpha + \frac{\ln\mu}{\rho})\mu < 0$, $\eta(\infty) > 0$ and $\dot{\eta}(t) > 0$, we obtain that $\beta\mathrm{e}^{\lambda\tau} + (\alpha + \frac{\ln\mu}{\rho} + \lambda)\mu = 0$ has a unique solution $\lambda > 0$.

According to (12), $\epsilon > 0$ and $\lambda > 0$, for $-\tau \leqslant t \leqslant 0$, it is obvious that we can obtain

$$\nu(t) \leqslant \frac{1}{\mu}\|\phi(t)\|_1 < \gamma\mathrm{e}^{-\lambda t} + \frac{\varepsilon}{-(\alpha+\frac{\ln\mu}{\rho})\mu - \beta}. \tag{23}$$

Next, we prove

$$\nu(t) < \gamma\mathrm{e}^{-\lambda t} + \frac{\varepsilon}{-(\alpha+\frac{\ln\mu}{\rho})\mu - \beta}, \quad t \geqslant 0. \tag{24}$$

If Eq. (24) is not true, there exists a $t^* > 0$ such that

$$\nu(t^*) \geqslant \gamma\mathrm{e}^{-\lambda t^*} + \frac{\varepsilon}{-(\alpha+\frac{\ln\mu}{\rho})\mu - \beta}, \tag{25}$$

and

$$\nu(t) < \gamma\mathrm{e}^{-\lambda t} + \frac{\varepsilon}{-(\alpha+\frac{\ln\mu}{\rho})\mu - \beta}, \quad t < t^*. \tag{26}$$

According to (22) and (26), we have

$$\begin{aligned} \nu(t^*) &\leqslant \gamma\mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})t^*} + \int_0^{t^*} \mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})(t^*-s)} \left[\frac{\beta}{\mu}\nu(s-\tau(s)) + \frac{\varepsilon}{\mu}\right]\mathrm{d}s \\ &< \mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})t^*} \left\{\gamma + \frac{\varepsilon}{-(\alpha+\frac{\ln\mu}{\rho})\mu - \beta} + \int_0^{t^*} \mathrm{e}^{-(\alpha+\frac{\ln\mu}{\rho})s} \left[\frac{\beta}{\mu}\nu(s-\tau(s)) + \frac{\epsilon}{\mu}\right]\mathrm{d}s\right\} \\ &< \mathrm{e}^{(\alpha+\frac{\ln\mu}{\rho})t^*} \left\{\gamma + \frac{\varepsilon}{-(\alpha+\frac{\ln\mu}{\rho})\mu - \beta} + \int_0^{t^*} \mathrm{e}^{-(\alpha+\frac{\ln\mu}{\rho})s} \left[\frac{\beta}{\mu}\left(\gamma\mathrm{e}^{-\lambda(s-\tau(s))}\right.\right.\right. \\ &\qquad \left.\left.\left. + \frac{\varepsilon}{-(\alpha+\frac{\ln\mu}{\rho})\mu - \beta}\right) + \frac{\varepsilon}{\mu}\right]\mathrm{d}s\right\} \end{aligned}$$

$$\leqslant \gamma \mathrm{e}^{-\lambda t^*} + \frac{\varepsilon}{-(\alpha + \frac{\ln \mu}{\rho})\mu - \beta}. \tag{27}$$

It is obvious that Eq. (27) contradicts (25) and thus Eq. (24) holds. By letting $\varepsilon \to 0$, we obtain

$$V(t) \leqslant \nu(t) \leqslant \gamma \mathrm{e}^{-\lambda t}, \quad t \geqslant 0. \tag{28}$$

In addition, we obtain

$$\|\epsilon(t)\|_1 \leqslant \frac{1}{\mu}\|\phi(t)\|_\tau \mathrm{e}^{-\lambda t}, \quad t \geqslant 0. \tag{29}$$

Because $\mu = \max_{k\in\mathbb{N}}\{|1+d_k|\} \in (0,1)$, from Definition 3, we conclude that error system (9) is globally exponential stable, i.e., the response system (4) is globally synchronized with master system (1). This completes the proof.

Remark 2. Eq. (11) shows a co-design approach between the controller gain and event-triggered mechanism, which is often used to select control gain k_2 and event-triggering parameter σ. From (11), once the parameters of the MNNs and event-triggered scheme are determined, k_2 can be selected easily.

Remark 3. Because the connection weight matrices $A_2(t)$, $A_1(t)$, $B_2(t)$, and $B_1(t)$ are related to system states, $A_2(t) \neq A_1(t)$ and $B_2(t) \neq B_1(t)$ occur when selecting different initial conditions. Thus, the mismatched terms $(A_2(t) - A_1(t))f(x(t))$ and $(B_2(t) - B_1(t))f(y(t-\tau(t)))$ do not equal zero. Here, the primary difficulty in achieving complete synchronization between systems (4) and (1) lies in dealing with the mismatched terms. Only the quasi-synchronization of MNNs can be guarantee by utilizing ETIC methods [37–39]. Inspired by [16, 17, 30], we adopt the sign term $-k_2 \operatorname{sign}(e(t_k))$ to compensate the mismatched terms, which is not used in existing event-triggered hybrid impulsive controllers [38, 39]. Moreover, the proposed event-triggered hybrid state feedback and impulsive control method can also be used to study the complete synchronization of heterogenous dynamic networks [13].

Remark 4. Note that $|1 + d_k|$ in Theorem 1 must satisfy $0 < |1 + d_k| < 1$ which is beneficial to synchronization control. The impulse sequence with $|1 + d_k| = 1$ means there is no action for error system (9) at moment t_k. When $|1 + d_k| > 1$, the term $|1 + d_k|e(t_k)$ can be considered as impulsive disturbance that degrades the stability of error system (9). Thus, the proposed method may be used to deal with ETC of systems with impulsive effects.

Remark 5. Differing from the switched systems under time-dependent switching [27], MNNs can be considered as types of state-dependent switching systems because the connection weights relate to the system states. Ref. [28] considers the event-based synchronization of uncertain systems, in which the parameter uncertainties are always identical for the master and slave systems. In addition, the weights matrices of the master system (1) and response system (4) are not the same before synchronization is realized. Therefore, compared to previous results [27, 28], the research in this study is more complicated.

Theorem 2. Considering error system (9) with controller (7), under event-triggered mechanism (10), the Zeno behavior can be excluded for system (9).

Proof. In the following proof, we assume $\epsilon(t) \neq 0$, because $\epsilon(t) = 0$ implies that synchronization has been achieved. For $t \in [t_k,\ t_{k+1})$,

$$\begin{aligned} D^+\|E(t)\|_1 &\leqslant \|\dot{E}(t)\|_1 = k_1\|\dot{\epsilon}(t)\|_1 \\ &= k_1\| - C\epsilon(t) + A_2(t)f(y(t)) - A_1(t)f(x(t)) + B_2(t)f(y(t-\tau(t))) \\ &\quad - B_1(t)f(x(t-\tau(t))) - k_1\epsilon(t_k) - k_2 \operatorname{sign}(\epsilon(t_k))\|_1 \\ &\leqslant k_1\|C\|_1\|\epsilon(t)\|_1 + 2k_1(\|\tilde{A}\|_1 + \|\tilde{B}\|_1)\|M\|_1 + k_1^2\|\epsilon(t_k)\|_1 + nk_1k_2, \end{aligned} \tag{30}$$

where $M = (M_1, M_2, \ldots, M_n)^{\mathrm{T}}$. Considering the definition of $E(t)$, we have

$$\begin{aligned} k_1\|C\|_1\|\epsilon(t)\|_1 &= \|C\|_1\|k_1\epsilon(t)\|_1 \\ &= \|C\|_1\|k_1\epsilon(t) + k_2 \operatorname{sign}(\epsilon(t)) - k_1\epsilon(t_k) - k_2 \operatorname{sign}(\epsilon(t_k)) - k_2 \operatorname{sign}(\epsilon(t)) + k_1\epsilon(t_k) + k_2 \operatorname{sign}(\epsilon(t_k))\|_1 \end{aligned}$$

$$\leqslant \|C\|_1(\|-E(t)\|_1 + \|-k_2\,\mathrm{sign}(\epsilon(t))\|_1 + \|k_1\epsilon(t_k)\|_1 + \|k_2\,\mathrm{sign}(\epsilon(t_k))\|_1)$$
$$\leqslant \|C\|_1\|E(t)\|_1 + k_1\|C\|_1\|\epsilon(t_k)\|_1 + 2nk_2\|C\|_1. \tag{31}$$

By combining (30) and (31), we obtain

$$D^+\|E(t)\|_1 \leqslant \|C\|_1\|E(t)\|_1 + \omega, \tag{32}$$

where $\omega = 2k_1(\|\tilde{A}\|_1+\|\tilde{B}\|_1)\|M\|_1+(k_1^2+k_1\|C\|_1)\|\epsilon(t_k)\|_1+nk_1k_2+2nk_2\|C\|_1$. Noting that $\|E(t_k)\|_1 = 0$, we obtain

$$\|E(t)\|_1 \leqslant \frac{\omega}{\|C\|_1}(\mathrm{e}^{\|C\|_1(t-t_k)} - 1), \quad t \in [t_k, t_{k+1}). \tag{33}$$

From the event-triggered condition (10), we obtain

$$\|E(t_{k+1})\|_1 \geqslant \sigma k_1\|\epsilon(t_{k+1})\|_1 + n\sigma k_2 \geqslant n\sigma k_2. \tag{34}$$

By combining (33) and (34), we obtain

$$n\sigma k_2 \leqslant \|E(t_{k+1})\|_1 \leqslant \frac{\omega}{\|C\|_1}(\mathrm{e}^{\|C\|_1(t_{k+1}-t_k)} - 1), \tag{35}$$

which implies

$$t_{k+1} - t_k \geqslant \frac{1}{\|C\|_1}\ln\left(\frac{n\sigma k_2\|C\|_1}{\omega} + 1\right) > 0. \tag{36}$$

Thus, we conclude that error system (9) can avoid Zeno behavior.

4 Numerical example

Here, a numerical example is discussed to demonstrate the effectiveness of the previous theoretical results.

Example 1. Consider the following MNN as a master system [39]:

$$\dot{x}_r(t) = -c_r x_r(t) + \sum_{l=1}^{n} a_{rm}(x_r(t))f_r(x_r(t)) + b_{rm}(x_r(t))f_r(x_r(t-\tau_r(t))), \quad r = 1, 2, \tag{37}$$

where $c_1 = c_2 = 1$, $a_{11}(x_1(t)) = 1.75$, $a_{22}(x_2(t)) = 2.85$, $b_{11}(x_1(t)) = -1.6$, $b_{22}(x_2(t)) = -2.38$,

$$a_{12}(x_1(t)) = \begin{cases} 2.9, |x_1(t)| \leqslant 2, \\ 2.8, |x_1(t)| > 2, \end{cases} \quad a_{21}(x_2(t)) = \begin{cases} -2.9, |x_2(t)| \leqslant 2, \\ -2.8, |x_2(t)| > 2, \end{cases}$$

$$b_{12}(x_1(t)) = \begin{cases} -0.08, |x_1(t)| \leqslant 2, \\ -0.11, |x_1(t)| > 2, \end{cases} \quad b_{21}(x_2(t)) = \begin{cases} -0.11, |x_2(t)| \leqslant 2, \\ -0.1, |x_2(t)| > 2, \end{cases}$$

$\tau_1(t) = \frac{\mathrm{e}^t}{\mathrm{e}^t+1}$, $\tau_2(t) = 0.75 - 0.5\sin(t)$, $f(x(t)) = [\tanh(x_1(t)), \tanh(x_2(t))]^{\mathrm{T}}$. Figure 1 shows the phase trajectory of system (37) with initial value $x(0) = [2.3, -1]^{\mathrm{T}}$.

The response system is represented as

$$\dot{y}_r(t) = -c_r y_r(t) + \sum_{l=1}^{n} a_{rm}(y_r(t))f_r(y_r(t)) + b_{rm}(y_r(t))f_r(y_r(t-\tau_r(t))) + u_r(t), \quad r = 1, 2, \tag{38}$$

where the parameters are the same as system (37).

It is obvious to see that $f_r(x_r(t))$ $(r = 1, 2)$ satisfy Assumption 1 with $l_r = 1$ and $M_r = 1$ $(r = 1, 2)$. Considering the definitions of $\tilde{A}$ and $\tilde{B}$, we obtain

$$\tilde{A} = \begin{pmatrix} 1.75 & 2.9 \\ 2.9 & 2.85 \end{pmatrix}, \quad \tilde{B} = \begin{pmatrix} 1.6 & 0.11 \\ 0.11 & 2.38 \end{pmatrix}.$$

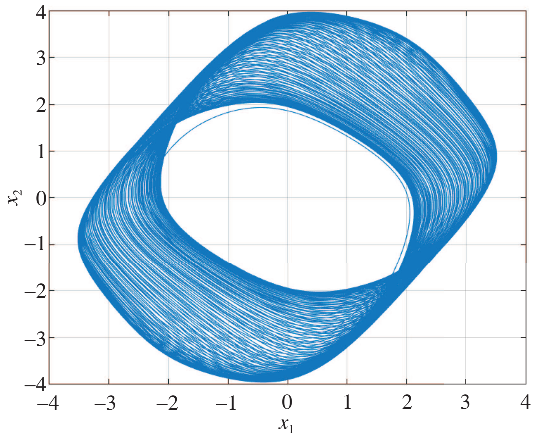

Figure 1 (Color online) Phase trajectory of system (37) with initial condition $x(0) = [2.3, -1]^{\mathrm{T}}$.

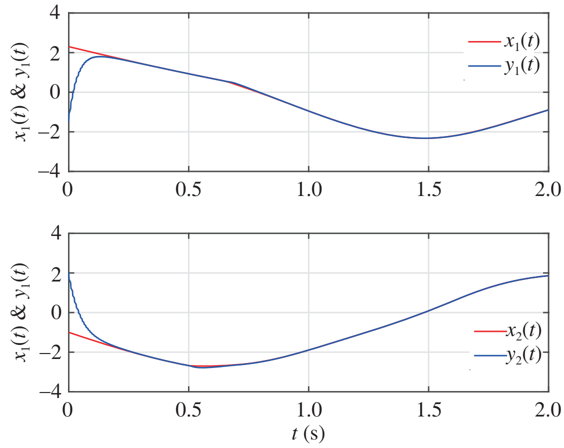

Figure 2 (Color online) Dynamic behaviors of states $x(t)$ and $y(t)$ in systems (37) and (38).

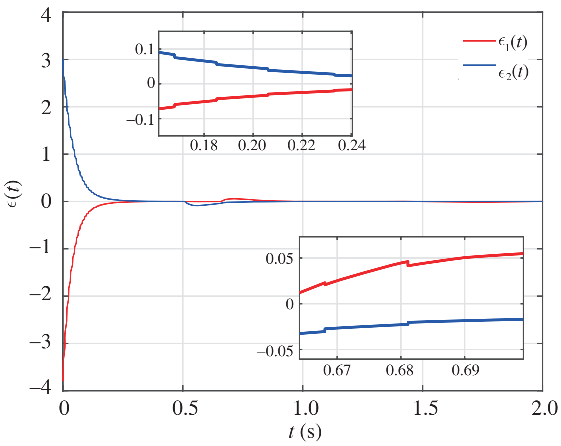

Figure 3 (Color online) Dynamic behaviors of errors between systems (37) and (38).

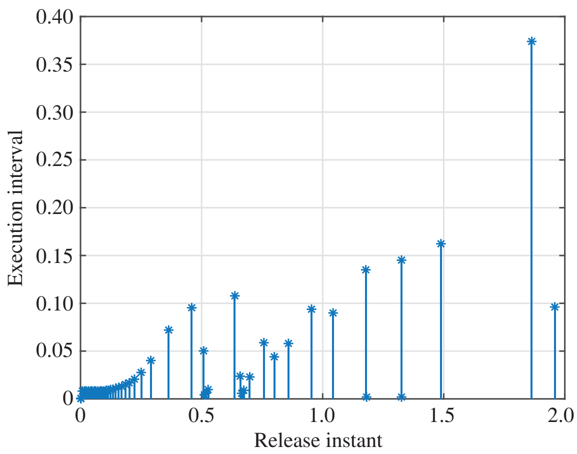

Figure 4 (Color online) Triggering release instants and execution intervals.

Owing to $\varpi_1 = 0.13$, $\varpi_2 = 0.11$, we select $k_2 = 0.4$. In addition, $\sigma = 0.2$, $d_k = -0.1$ ($k \in \mathbb{N}$), $\rho = 0.5$ and $k_1 = 9.2$ are selected. Note that we can evaluate whether the conditions in Theorem 1 are satisfied, which implies that synchronization between the master MNN (37) and response MNN (38) is realized.

Next, we provide simulation results. Here, the initiation values of systems (37) and (38) are $x(t) = [2.3, -1]^{\mathrm{T}}$ and $y(t) = [-1.5, 2]^{\mathrm{T}}$, respectively. Figure 2 shows the state curves of systems (37) and (38). And Figure 3 shows the dynamic of the error system. As shown in Figure 3, the error state curves converge to zero, which means that synchronization between systems (37) and (38) is realized. Figure 4 shows the release instants. As can be seen, fewer signals are transmitted.

Remark 6. The system parameters selected in Example 1 are the same as the numerical example in [39]. Under the event-triggered impulsive controller (7) given in [39], quasi-synchronization can be realized. Controller (7) designed in the current paper can achieve the complete synchronization of MNNs. Figure 3 shows that the synchronization errors converge to zero, which demonstrates the effectiveness of the designed controller (7) here.

5 Conclusion

In this paper, the issue for the synchronization of MNNs is investigated. Compared with existing results, a new kind of event-triggered hybrid impulsive controller is designed to guarantee the complete synchronization of MNNs. By using the Lyapunov functional method, a synchronization criterion is given to guarantee the synchronization between the master MNN and the response. The Zeno behaviour can be excluded and the theoretical analysis is provided. A numerical example is given to show the effectiveness of derived results.

Note that the results for the proposed event-triggered hybrid impulsive synchronization control design may be applicable to finite-time [43, 44], dynamic event-triggered transmission [45] and networked signal transmission [46, 47] cases, which will be the focus of future work.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant No. 61973166) and Fundamental Research Funds for the Central Universities (Grant No. 30919011409).

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