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Desynchronization in synchronous multi-coupled chaotic neurons by mix-adaptive feedback control

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In this paper, by means of the invariance principle of differential equations, an adaptive feedback scheme is proposed to realize desynchronization in synchronous multi-coupled chaotic neurons by the mix-adaptive feedback effectively. Numerical simulations for the Hindmarsh–Rose neural model with self-coupling are illustrated which agree well with our theoretical analysis. It is observed that the feedback strengths asymptotically converge to a local fixed value in finite time, especially for linear coupling chaotic neurons with self-coupling. Furthermore, robustness of desynchronization in three coupled chaotic neurons on small mismatch of parameters is shown.

Keywords: desynchronization; adaptive delay feedback; neural activity; synaptic coupling strengths; neuronal network; feedback strength

2000 Mathematics Subject Classifications: 92B20, 93C40

1. Introduction

Neurons and neural networks can be modelled by differential equations and dynamical systems at many different levels, depending upon diverse phenomena and the accuracy desired. They have been gaining increasing attention and recognition as a fundamental tool in understanding dynamical behaviours and response of real systems coming from different fields such as biology, social systems, linguistic networks, and technological systems [1,15,23,32]. How to understand the synchronous activity in neurons has been an interesting subject in interdisciplinary sciences. Living tissues are complex organizations of individual cells. The activity of each cell within the tissue should be regulated in a coordinated manner to perform their specific functions. Synchronous activities in the central nervous system are the collective behaviours in the process of information transmission, so as to form a coherent and unified perception of the external world [4,9,28]. Though the mechanism during the regulation process is very complex, a regular way is to exert control on neural transmission to change the neuron’s activity.

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The dynamics of neural networks have been widely investigated, with special emphasis on the interplay between the complexity in the overall topology and the local dynamical properties of the coupled nodes [7,18,25]. As a typical kind of dynamics, synchronization and desynchronization in neural networks have become of significant interest in recent years. One of particular aims is to understand how synchronization and desynchronization depends on various parameters of the network, such as average distance, clustering coefficient, coupling strength, degree distribution, weight distribution, etc. [2,3,8,14,17,26,29]. Different types of synchronization such as complete synchronization [6], phase synchronization [21], lag synchronization [17,22], almost synchronization [5], chaotic synchronization [27], and anticipated synchronization [33] have been described. Desynchronization is a process inverse to synchronization, where initially synchronized oscillating systems desynchronize as parameters change or they do so under the influence of an external force or feedback. Desynchronization is important. For example, in neuroscience and medicine, pathologically strong synchronization of neurons may severely impair the brain function as, for example, in Parkinson’s disease or epilepsy [20,24,30,34]. Effective desynchronization has been exploited as a tool for probing the functional significance of synchronized neural activity underlying perceptual and cognitive processes or as a mild treatment for neurological disorders like Parkinson’s disease [13,19].

Recently, extensive works have been done towards understanding the synchronization of globally coupled phase oscillators, and in particular, possible methods for desynchronizing such systems with short sequences of pulses [11,31,35]. In [11], an adaptive feedback scheme was proposed to achieve complete synchronization. Based on this feedback scheme, adaptive synchronizations of neural networks with or without delay were described [31,35]. This proposed scheme appears simple and is robust against the effect of small noise. It is of great importance for the treatment of neurological disorders like Parkinson’s disease and essential tremor, and can also be used to design new psychophysiological and cognitive experimental techniques. In these studies, considering transmission delay in some neural models becomes necessary. In practice, the information is not instantaneous in general because of the finite propagation velocity and delay in the transmission of signal, thus the delay should be an indispensable factor in these circumstances. In our previous works [17,29], we once explored synchronization for neural networks with time delay by using the theory of asymptotic stability. In the present paper, we develop an adaptive feedback scheme to study desynchronization in synchronous multi-coupled chaotic neurons.

The rest of the paper is organized as follows. In Section 2, a theoretic result is presented on desynchronization in synchronous multi-coupled chaotic neurons. As an example, a model of three coupled Hindmarsh–Rose (HR) neurons is discussed by the adaptive feedback scheme. Furthermore, we find that small mismatch parameters on the effects of the desynchronization are robust. Section 3 is a brief conclusion.

2. Main results

2.1. Analytical theorem

In this section, based on the invariance principle of differential equations [12], we are concerned with desynchronization in synchronous multi-coupled chaotic neurons with the mix-adaptive delay feedback. Consider the following synchronous multi-coupled chaotic neural system:

$$\dot{x}_i = f(x_i) + \varepsilon H_i(x_1, x_2, \ldots, x_i, \ldots, x_n),$$

where $x_i = (x_{i1}, x_{i2}, \ldots, x_{in})^T \in \mathbb{R}^n$, $f(x_i) = (f_{i1}(x_i), f_{i2}(x_i), \ldots, f_{in}(x_i))^T$ is a nonlinear vector function, and $H_i$ may be linear or nonlinear. We called Equation (1) the reference system.
Let $\Omega \subset \mathbb{R}^n$ be a chaotic bounded set of system (1), which is globally attractive. In general, we assume that 

(I) the nonlinear vector function $f(x_i)$ is globally Lipschitz with positive constants $l > 0$ such that $|f_i(x) - f_i(y)| \leq l|x - y|$ for any $x(t), y(t) \in \mathbb{R}^n$,

(II) $H(x_1, x_2, \ldots, x_i, \ldots, x_n)$ is local Lipschitz with positive constants $m_i$ such that 

$$|H_i(x_1, x_2, \ldots, x_i, \ldots, x_n) - H_i(y_1, y_2, \ldots, y_i, \ldots, y_n)| \leq \sum_{i=1}^{n} m_i |x_i - y_i|.$$ 

In what follows, we consider the system of multi-coupled chaotic neurons with the mix-adaptive feedback in the form

$$\dot{y}_i = f(y_i) + \varepsilon H_i(y_1, y_2, \ldots, y_i, \ldots, y_n) + u_i, \quad (2)$$

where $y_i$ represents the response state, $u_i$ represents the feedback control with the delayed state $u_i = k_i(x_i(t - \tau_i) - y_i)$. We called it the controlled system. From [11,31], the feedback strength $k_i = (k_{i1}, k_{i2}, \ldots, k_{in})^T$ is adapted according to the following scheme [35]:

$$\dot{k}_i = \gamma_i (x_i(t - \tau_i) - y_i)^2, \quad i = 1, 2, \ldots, n, \quad (3)$$

where $\tau_i \neq \tau_j$ and $i \neq j$.

Let $e_i^{\tau_i} = x_i(t - \tau_i) - y_i$ and $x_i(t - \tau_i) = x_i^{\tau_i}(t)$. Apparently, if $\tau_i = 0$, then $e_i = x_i - y_i$. From Equations (1) and (2) we deduce that

$$\dot{e}_i^{\tau_i} = f(x_i^{\tau_i}(t)) - f(y_i) + \varepsilon (H_i(x_1^{\tau_i}, x_2^{\tau_i}, \ldots, x_i^{\tau_i}, \ldots, x_n^{\tau_i}) - H_i(y_1, y_2, \ldots, y_i, \ldots, y_n)) - k_i e_i^{\tau_i}. \quad (4)$$

**Definition 1** For systems (1) and (2), we say that they possess the property of desynchronization, if there exists $e_i^{\tau_i} \to 0$ as $t \to +\infty$, $i = 1, 2, \ldots, n$.

**Theorem 1** Assume that conditions (I) and (II) hold, and systems (1) and (2) satisfy the adaptive scheme (3). Then desynchronization in synchronous coupled chaotic neurons can be achieved, that is, $\lim_{t \to +\infty} e_i^{\tau_i} = 0$, $i = 1, 2, \ldots, n$.

**Proof of Theorem 1** According to Equations (3) and (4), we construct a Lyapunov function as

$$E_h(t) = \frac{1}{2} \sum_{i=1}^{n} (e_{ih}^{\tau_i})^2 + \frac{1}{2} \sum_{i=1}^{n} \frac{1}{f_{ih}} (k_{ih} + L)^2, \quad h = 1, 2, \ldots, n,$$

where $L$ is a constant and $L + l + \varepsilon ((n + 1)m_i/2) < 0$. Calculating the derivative of $E_h(t)$ along the trajectory of the error system (4) yields

$$\frac{dE_h(t)}{dt} = \sum_{i=1}^{n} e_{ih}^{\tau_i} \dot{e}_{ih}^{\tau_i} + \sum_{i=1}^{n} (k_{ih} + L)(e_{ih}^{\tau_i})^2$$

$$\leq \sum_{i=1}^{n} (l + L)(e_{ih}^{\tau_i})^2 + \varepsilon \sum_{i=1}^{n} e_{ih}^{\tau_i} \sum_{j=1}^{n} m_j |e_{jh}|^{\tau_j}$$

$$\leq \sum_{i=1}^{n} (l + L)(e_{ih}^{\tau_i})^2 + \varepsilon \sum_{i=1}^{n} \sum_{j=1}^{n} m_j \left(\frac{(e_{ih}^{\tau_i})^2 + (e_{jh}^{\tau_j})^2}{2}\right)$$

$$= \sum_{i=1}^{n} \left[ l + L + \varepsilon \frac{(n + 1)m_i}{2} \right] (e_{ih}^{\tau_i})^2$$

$$\leq 0.$$
If and only if $e_{ih}^\tau_i$ are all equal to zero, then we have $dE_h(t)/dt = 0$. Thus, we have $\lim_{t \to \infty} e_{ih}^\tau_i = 0$, that is, $y_i(t) = x_i(t - \tau_i)$, $i, j = 1, 2, \ldots, n$.

**Remark 1** According to above proposed desynchronization scheme, we can obtain desynchronization in synchronous coupled chaotic neurons effectively. The above result appears rather general.

### 2.2. Applications to HR models

In this section, we consider a model of the HR neurons [10] described by the following equations:

$$
\begin{align*}
\dot{x}_1 &= x_2 - ax_1^3 + bx_1^2 - x_3 + I_x, \\
\dot{x}_2 &= c - dx_2^2 - x_2, \\
\dot{x}_3 &= r[s(x_1 - \bar{x}) - x_3],
\end{align*}
$$

where $x_1$ represents the membrane potential, $x_2$ represents a recovery variable associated with the fast current, $x_3$ denotes the adaption current, and $a, b, c, d, r, s$, and $\bar{x}$ are real constants. In our previous work [16], we studied the stability by classifying neighbourhood regimes near the Fold-Hopf points and illustrated the complex bursting-spiking firing modes associated with Fold-Hopf bifurcations by numerical simulations. Here we take $a = 1.0$, $b = 3.0$, $c = 1.0$, $d = 5.0$, $s = 4.0$, $\bar{x} = -1.60$, $r = 0.005$ and choose $I_x$ as a control parameter. The change of the value of $I_x$ causes rich firing behaviours. System (5) exhibits multiple time-scale chaotic bursting behaviours for $1.47 < I_x < 3.45$, especially in the case of $I_x = 3.2$ (Figure 1).

For convenience, we consider the system of three coupled chaotic HR neurons for two cases (Figure 2).

**Case (a):** ring coupling chaotic neurons with self-coupling. Consider the system of three ring-coupled chaotic HR neurons with self-coupling:

$$
\begin{align*}
\dot{x}_{1i} &= x_{i2} - ax_{1i}^3 + bx_{1i}^2 - x_{i3} + I_x + \epsilon H_i(x_{i1}, x_{i2}, x_{i3}), \\
\dot{x}_{2i} &= c - dx_{2i}^2 - x_{i2}, \\
\dot{x}_{3i} &= r[s(x_{i1} - \bar{x}) - x_{i3}],
\end{align*}
$$

Figure 1. (a) Chaotic bursting of HR model at $I_x = 3.2$; (b) chaotic attractor of HR model.
Figure 2. (a) Ring coupling chaotic neurons with self-coupling; (b) linear coupling chaotic neurons with self-coupling.

Figure 3. The portrait of system (6) with respect to ring coupling chaotic neurons with self-coupling for $\varepsilon = 2.0$.

where $x_i = (x_{i1}, x_{i2}, x_{i3})$, $i = 1, 2, 3$, relevant parameter values are the same of system (5), and

$$(H_1, H_2, H_3) = \begin{pmatrix} -1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \end{pmatrix} (x_{11}, x_{21}, x_{31})^T.$$

When $\varepsilon = 2.0$, synchronization has been achieved, the corresponding numerical results are shown in Figure 3. As real coupled neurons are concerned, the information from the presynaptic neuron is transmitted to the postsynaptic one with certain time delay. Time delays are
Figure 4. (a)–(c) Desynchronization for three ring-coupled chaotic neurons with the delay $\tau_1 = 25$ and $\tau_3 = 50$, respectively; (d) the temporal evolution of $k_1$, $k_2$, and $k_3$ for $I_x = I_y = 3.2$.

inherent in neuronal transmissions. Thus it is important to seek the controlling method of synchronous neurons.

In what follows, the corresponding three coupled chaotic neurons are described by the following system:

$$
\begin{align*}
\dot{y}_1 &= y_2 - ay_1^3 + by_1^2 - y_3 + I_y + \epsilon H_i(y_{11}, y_{21}, y_{31}) + k_ie_{1i}^{\tau_i}, \\
\dot{y}_2 &= c - dy_2^2 - y_2, \\
\dot{y}_3 &= r[s(y_{11} - \bar{y}) - y_3], \\
\end{align*}
$$

(7)

where $y_i$ represents the response state, $\tau_i$ represents time delay, $e_i = x_i - y_i$, $e_i^{\tau_i} = x_i(t - \tau_i) - y_i$, and $e_i = (e_{1i}, e_{2i}, e_{3i})$. In order to discuss the synaptic effect to the membrane potential through the gap junction between neurons, we take the synaptic coupling strength as $k_i$. Here the feedback strength $k_i$ is adapted according to the following scheme:

$$
\begin{align*}
\dot{k}_2 &= \gamma_2(x_{21} - y_{21})^2, \\
\dot{k}_i &= \gamma_i(x_{i1}(t - \tau_i) - y_{i1})^2, \quad i = 1, 3.
\end{align*}
$$

(8)
Figure 5. (a)–(c) Desynchronization for three ring-coupled chaotic neurons with the delay $\tau_1 = 25$ and $\tau_3 = 50$, respectively; (d) the temporal evolution of $k_1$, $k_2$, and $k_3$ for $I_x = 3.2$ and $I_y = 3.18$.

We take parameters $\gamma_i = 0.1$, $i = 1, 2, 3$, $I_x = I_y = 3.2$, and the initial feedback strength 0.01 to investigate desynchronization in the system of three synchronous coupled chaotic neurons.

The corresponding numerical simulations are shown in Figure 4. It is shown in Figure 4(a)–(c) with the delay $\tau_1 = 25$ and $\tau_3 = 50$, respectively, that the coupled system achieves desynchronization by using the mix-adaptive feedback control. Furthermore, from Figure 4(d), the feedback strength $k_1$, $k_2$, and $k_3$ asymptotically converges to a local fixed value, respectively.

Nonidentity exists everywhere in nature. Thus, it is useful to investigate destructuralization in three coupled HR chaotic neurons with the small mismatch of parameters. We take $I_x = 3.2$ and $I_y = 3.18$, respectively. It is presented in Figure 5(a)–(c) with the delay $\tau_1 = 25$ and $\tau_3 = 50$, respectively, that desynchronization of the coupled system can be achieved by using the mix-adaptive feedback control. Furthermore, we can observe the robustness of feedback strength of desynchronization by comparing Figure 4(d) with Figure 5(d).

Case (b): linear coupling chaotic neurons with self-coupling.
Figure 6. The synchronization portrait of system (6) with respect to linear coupling chaotic neurons with self-coupling for $\varepsilon = 2.0$. 

Figure 7. (a)–(c) Desynchronization for three linear coupled chaotic neurons with the delay $\tau_1 = 25$ and $\tau_3 = 50$, respectively; (d) the temporal evolution of $k_1, k_2,$ and $k_3$ for $I_x = I_y = 3.20$. 
Similar simulations can be obtained for linear coupling chaotic neurons with self-coupling. In Figure 6, simulations for linear coupling chaotic neurons with self-coupling are illustrated. It is shown from Figure 7(a)–(c) with the delay $\tau_1 = 25$ and $\tau_3 = 50$, respectively, that desynchronization of the coupled system can be achieved by applying the mix-adaptive feedback control. In particular, the feedback strength can be a stable fix value (Figure 7(d)). Similarly, desynchronization in three linear coupled chaotic neurons on the small mismatch of parameters is also robust.

3. Conclusion

In this paper, we applied an adaptive feedback method to determine the desynchronization condition of neural systems, which enables us to observe desynchronization in synchronous multi-coupled chaotic neurons. Based on the invariance principle of differential equations and matrix inequality, applying the mix-adaptive feedback we obtained desynchronization in synchronous multi-coupled chaotic neurons. Numerical simulations are in agreement with our analytical result.

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