



Cluster synchronization and rhythm dynamics in a complex neuronal network with chemical synapses



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ABSTRACT

Cluster synchronization and rhythm dynamics are studied for a complex neuronal network with the small world structure connected by chemical synapses. Cluster synchronization is considered as that in-phase burst synchronization occurs inside each group of the network but diversity may take place among different groups. It is found that both one-cluster and multi-cluster synchronization may exist for chemically excitatory coupled neuronal networks, however, only multi-cluster synchronization can be achieved for chemically inhibitory coupled neuronal networks. The rhythm dynamics of bursting neurons can be described by a quantitative characteristic, the width factor. We also study the effects of coupling schemes, the intrinsic property of neurons and the network topology on the rhythm dynamics of the small world neuronal network. It is shown that the short bursting type is robust with respect to the coupling strength and the coupling scheme. As for the network topology, more links can only change the type of long bursting neurons, and short bursting neurons are also robust to the link numbers.

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1. Introduction

There are about 10^{10} neurons with 10^{14} links between them in a human brain forming a complex network [1]. An emergent property of this dynamical system is that a set of neurons synchronize and fire impulses simultaneously. Neuronal synchronization plays a vital role in mechanisms of information processing within different brain area [2–4]. It is also suggested that synchronization is the origin of neurological diseases such as epilepsy [5] and Parkinson's disease [6]. As for neural networks, neuronal synchronization results from the interplay between the intrinsic properties of individual neurons, the properties of synaptic coupling, as well as the network topology. Each of them may play an important role in shaping the emergent synchronous behaviors and it is important to determine the precise role each factor plays.

Diverse electrical spike activities of neurons can be observed in experiments and model simulations. These activities may be in the state of tonic spiking, or be organized in bursts in which time intervals with high spiking rates are separated by others with much lower spiking rates. In developing mathematical measures for neuronal activities, a key issue is how to characterize the bursting patterns. The width factor is introduced in Ref. [7] to

describe the bursting dynamics and classify the bursting patterns into two types, that is, long and short burstings.

Recently, cluster synchronization has attracted increasing attention due to its applications in biological science and communication engineering [8–12]. Cluster synchronization is considered to be more momentous than complete synchronization in brain science [13]. As a particular synchronization phenomenon, cluster synchronization requires that synchronization occurs inside each group, but there is no synchronization among the different groups. Nowadays, this phenomenon is mainly investigated when complete synchronization occurs in each cluster of the network. However, for neuronal networks, a more important synchronization state is burst synchronization, which means that neurons emit bursts with fixed burst phase differences. Hence, this work concerns with cluster synchronization when in-phase burst synchronization is realized in each cluster but the burst phases may be different among clusters.

Watts and Strogatz showed that many complex networks in real world have small-world property with high degrees of clustering in their famous paper [14]. Although neurons are sparsely connected in brain, they are within only a few synaptic steps from all other neurons and their underlying network has small-world property [1]. Studies of neuronal firing activities are based on neuronal models which can be divided into two categories: ordinary differential equations based models and map-based ones [15]. There have been many differential equations

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based models, especially the famous Hodgkin–Huxley neuron model. There also are a number of map-based neuron models, including the Rulkov model [16]. Without being biophysically meaningful, the Rulkov model not only has been shown to be capable of producing many of the observed neuronal behaviors such as tonic spiking, tonic bursting and chaotic firing as the Hodgkin–Huxley-type models but also can simplify analysis and speed up computations greatly. Therefore, one could have a great advantage in understanding the collective behavior of real world neuronal populations by studying the networks of Rulkov discrete-time systems.

Bursting is important since it is considered to enhance the reliability of communications between neurons by facilitating transmitter release [17,18]. The study of bursting rhythm of neuronal networks has attracted more and more interests in recent years [7,19–24,29,31]. Ref. [23] discussed how synchronization in a group of chaotically bursting nervous cells can lead to the onset of regular bursting by using a two-dimensional map of chaotic neurons. Batista et al. [22,25] investigated the burst synchronization in a scale-free and non-locally coupled network, in particular the dependence of chaotic phase synchronization on the coupling properties of network as well as the synchronization under an externally applied time-periodic signal.

Spatiotemporal order, that is, temporal coherence and spatial synchronization, is one of the most attractive phenomena of coupled non-linear elements [26–30]. Ordering spatiotemporal chaos of small world neural networks with electrical synaptic coupling have been studied extensively [26,28–31] in recent years. The above results, based on bursting neurons (chaotic or non-chaotic) as basic units of networks, presented some quantitative characteristics to evaluate the spatiotemporal order degree of neuronal networks. However, the rhythm dynamics of complex networks has not been considered completely.

In this work, we mainly investigate the effects of the rhythm properties and the coupling schemes (that is, excitatory and inhibitory) on cluster synchronization and rhythm dynamics of complex neuronal networks. An outline of this paper is given as follows. The Rulkov map-based neuron model and a complex neuronal network with chemical coupling and small world structure are introduced in Section 2. A basic characteristic of burst dynamics is also presented. The cluster synchronization of the complex neuronal networks with chemically excitatory and inhibitory coupling is studied in Section 3. The rhythm dynamics of the complex neuronal networks is presented in Section 4. Finally, conclusions are given in Section 5.

2. Model description

2.1. Rulkov neuron model

Bursting, in which rapid spiking states are followed by quiescence, is a general phenomenon of the activation patterns of neurons in the central nervous system and is thought to be important in the operation of robust central pattern generators [32,33], the transmission of neural codes [34] and some neuro-pathologies, such as epilepsy.

The models of bursting neurons always present multiple time scales, that is, fast variables relating to the action-potential firing (spiking) and slow processes modulating the fast ones to generate bursting.

Now consider the neuron model proposed by Rulkov [16], which is a two-dimensional discrete time map system with fast and slow time scales and spiking–bursting behaviors. The Rulkov model is given as follows:

$$x_{n+1} = F_{\alpha}(x_n, y_n)$$

$$y_{n+1} = y_n - \mu(x_n + 1) + \mu\sigma \quad (1)$$

where x represents the transmembrane voltage of the neuron and y the slow gating process. The difference between the time scales of the two subsystems is determined by a sufficiently small value of the parameter μ with $0 < \mu \ll 1$. The parameter σ describes the dc current injected into the cell. The non-linear function $F_{\alpha}(x, y)$ is responsible for the generation and reset of spikes, and is given by

$$F_{\alpha}(x, y) = \begin{cases} \frac{\alpha}{1-x} + y & \text{if } x < 0, \\ \alpha + y & \text{if } 0 \leq x < \alpha + y, \\ -1 & \text{if } x \geq \alpha + y. \end{cases}$$

Depending on the values of the parameters α and σ , the model of Rulkov's map can reproduce a variety of neuronal spiking–bursting activities. In this study, we fix $\alpha = 5.0$, $\mu = 0.001$ and control the value of σ to generate various regular neuronal firing patterns.

2.2. Rhythm dynamics of a single neuron

Some classification of bursting behaviors of single-neuron models have been developed by investigating the bifurcation structures of the fast and slow subsystems. However, it is also possible for bursting to arise through interactions between different parts inside a neuron or different clusters of neurons in a network. So further studies on bursting behavior both at the cellular and the network levels are interesting and necessary.

A characteristic quantity, which is called the width factor, is introduced to describe the bursting rhythm dynamics of a single neuron. It is defined as the average ratio between the duration of a burst T_b and the subsequent period of refractory time T_r , and denoted by $f = T_b/T_r$. If the width factor $f = T_b/T_r > 1$, this type of bursts is called long ones. Otherwise, the type of bursts with the width factor $f = T_b/T_r < 1$ is called short ones. By using directly calculation, we obtain that the width factor is larger than 1 after $\sigma = 0.14$ as shown in Fig. 1(a), which implies that the neuron transits from short bursting to long bursting at this critical value $\sigma = 0.14$. Therefore, with the external input increasing, the firing pattern of the neuron transits from short bursting to long bursting. We give the illustration of these two types of bursting in Fig. 1(b).

2.3. The small world complex neuronal network model with chemical synapses

The complex neuronal network is consisted of neurons described by the following maps:

$$x_{i,n+1} = F_{\alpha}(x_{i,n}, y_{i,n} + \beta_{i,n}), \quad (2)$$

$$y_{i,n+1} = y_{i,n} - \mu(x_{i,n} + 1) + \mu\sigma_i,$$

where the indices $i = 1, 2, \dots, M$ and $n = 1, 2, \dots, N$, which represent the i -th neuron and the discrete time, respectively. The coupling among neurons is provided by the currents toward the i -th neuron from others with $\beta_{i,n}$ as the coupling term. In what follows, the coupling is modeled by

$$\beta_{i,n} = -g_c a_{ij} H(x_{j,n} - \theta)(x_{i,n} - \nu), \quad i \neq j. \quad (3)$$

through reciprocal chemical synapse that follows the fast threshold modulation (FTM) model [35], where the summation abbreviation rule for the index j is used. g_c is the coupling strength mimicking the maximal conductance and $H(\cdot)$ is the Heaviside step function with $H(x) = 1$ if $x > 0$ and $H(x) = 0$ if $x \leq 0$. The parameter θ is the presynaptic threshold for chemical synaptic interaction. Only when the voltage of the presynaptic neuron is above θ does the postsynaptic neuron receive an external input. We choose

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