

Firing synchronization of learning neuronal networks with small-world connectivity

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ABSTRACT

The properties of firing synchronization of learning neuronal networks, electrically and chemically coupled ones, with small-world connectivity are studied. First, the variation properties of synaptic weights are examined. Next the effects of the synaptic learning rate on the properties of firing rate and synchronization are investigated. The influences of the coupling strength and the shortcut probability on synchronization are also explored. It is shown that synaptic learning suppresses over-excitement for the networks, helps synchronization for the electrically coupled neuronal network but destroys synchronization for the chemically coupled one. Both introducing shortcuts and increasing the coupling strength are helpful in improving synchronization of the neuronal networks. The spatio-temporal patterns illustrate and confirm the above results.

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1. Introduction

A human brain is composed of 10^{11} neurons, and each neuron in the cortex connects to more than 10,000 neurons via synapses [1]. Such a number of neurons and synapses constitute a very huge and complicated network. The findings of small-world connectivity [2] in some biological neuronal networks [3,4] support a conjecture that the brain has small-world structure. In the recent years many researches have been undertaken on small-world neuronal networks, e.g. [5–7].

Coupled neurons in a human brain exhibit various dynamical activities [8]. It is believed that studying these dynamical properties is instructive for exploring working mechanisms of a human brain. Lu et al. [9] reviewed the recent study of dynamics of neuronal firing activities and discussed various experimental and theoretical findings. Among such many dynamical phenomena, synchronous firing of neurons is thought to play a key role in information communication in neuronal systems. Many investigations were devoted to the study of synchronization of neuronal networks. Masuda and Aihara [10] studied global and local synchronization of pulse-coupled leaky integrate-and-fire neurons in small-world networks. It was found that the parameter of rewiring probability could transform the states of the networks

from precise local synchrony into rough global synchrony, and the interactions between the global connections and the local clustering forced synchronization of distant neuronal groups, which were receiving coherent inputs. Kitajima and Kurths [11] investigated the effect of noise on synchronization of a globally coupled neuronal network with external inputs. It was shown that small noise could improve synchronization of neural systems. Wang et al. [12] investigated ordered bursting synchronization of a chemically coupled neuronal network with ring structure, and found that the system could achieve ordered bursting synchronization by increasing the coupling strength and bursting synchronization could transform into spike synchronization under certain noise intensity.

However, most of the researches on neuronal networks are focused on the above mentioned aspects without learning, namely, the weights of synapses keep constant, which are plausible in real situations. In biological neuronal networks, the weights of synapses keep changing in the growth of cells and in the studying and memorizing processes of brain. This property is called synaptic plasticity. It has been commonly accepted that synaptic plasticity is the main mechanism of learning in human brain and plays an important role in some physiological or pathological processes such as regulation of cardiovascular system. For simulating synaptic plasticity in neural systems, many simplified learning rules, such as the Hebbian learning rule, the Oja rule, the STDP (spike-timing-dependent plasticity) rule and others [13], are proposed in artificial neural networks. There has been some researches on dynamics of neural systems with

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learning synapses. Zhigulin et al. [14] investigated the effects of spike-timing-dependent plasticity (STDP) on synchronization of two coupled neurons and found that the plasticity expanded the range of frequency locking and made synchronization faster. Kube et al. [15] applied STDP rule in a small-world neuronal network and found that the rule made the network less synchronous. It was also found that network with a large shortcut probability is robust to the introduction of shortcuts and the resulting distribution of the synaptic weights in single neurons had depended both on the global statistics of firing dynamics and on the number of incoming and outgoing connections.

This paper aims to explore the properties of firing synchronization in learning small-world neuronal networks. We apply a learning rule in electrically coupled and chemically coupled neuronal networks, respectively, and study the effects of various parameters on the properties of firing rates and synchronization of networks. This paper is organized as follows. Section 2 introduces the mathematical models of the learning small-world Hindmarsh–Rose neuronal networks. Section 3 presents the simulation results for firing rate and synchronization of electrically and chemically coupled neuronal networks. The conclusions are given in Section 4.

2. The neuronal models

Dynamics of real neurons are usually described by firing activities of neuronal models. The Hindmarsh–Rose (HR) neuronal model [16,17] is adopted in this paper as a typical example of real neurons, which can be expressed by the following equations:

$$\begin{aligned} \dot{x} &= y - ax^3 + bx^2 - z + I, \\ \dot{y} &= c - dx^2 - y, \\ \dot{z} &= r[s(x - \chi) - z], \end{aligned} \quad (1)$$

where x is the membrane potential, y is associated with the fast current of the Na^+ or K^+ ions, z is associated with the slow current of, for example, the Ca^{2+} ions, I is the stimulus current, which is delivered to the neuron from its external environment. The parameters are chosen as $a=1$, $b=3$, $c=1$, $d=5$, $s=4$, $r=0.006$, $\chi=-1.6$ and $I=3$, under which HR neuronal model exhibits a multiple time-scale chaotic bursting behavior, as shown in Fig. 1.

Assuming a HR neuron as a node, Newman–Watts (NW) strategy [18,19] is adopted to construct small-world neuronal networks. NW small-world strategy works like this: we start with

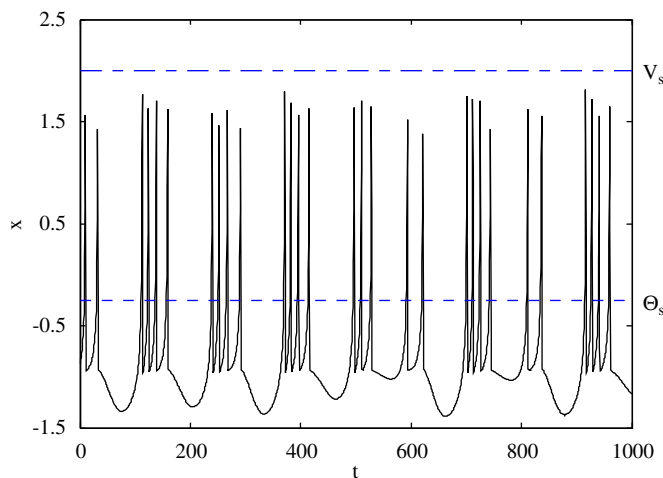


Fig. 1. Membrane potential of the HR neuronal model (with two thresholds used for modeling chemical synapses).

a ring of N neurons in which each neuron coupled to its k nearest neighbors, then we add shortcuts between pairs of neurons with shortcut probability p where $p \in (0, 1)$. As special cases, for $p=0$ we have the original regular network, or for $p=1$ a globally coupled network. The overall number of neurons is set as $N=100$, $k=8$ in this paper. The formation of a small-world neuronal network is presented in Fig. 2, where the nodes denote neurons and the connections denote synapses. Based on the network structure, a connectivity matrix $\mathbf{G}=\{g_{ij}\}_{N \times N}$ can be defined. If neuron i is connected with neuron j ($i \neq j$), then $g_{ij}=1$, otherwise, $g_{ij}=0$. As the connections are symmetric, the coupling matrix \mathbf{G} has the following properties: (1) \mathbf{G} is a symmetric and irreducible matrix. (2) The off-diagonal elements g_{ij} ($i \neq j$) of \mathbf{G} are either 1 or 0. (3) The diagonal elements $g_{ii} = -\sum_{j=1, j \neq i}^N g_{ij}$. (4) The eigenvalues of \mathbf{G} satisfy $0=\gamma_0 > \gamma_1 \geq \dots \geq \gamma_{N-1}$.

As mentioned earlier there are two types of synapses in nervous systems, electrical synapses and chemical synapses. In an electrical synapse, the presynaptic and postsynaptic cell membranes are connected by channels that are capable of passing electrical currents, causing voltage changes in the presynaptic cell to induce voltage changes in the postsynaptic cell. Electrical synapses can be described as linearly proportional to the potential difference between pre and postsynaptic neurons and the according coupling function of two neurons is presented as $f(x_i, x_j) = x_j - x_i$, where i and j denote the pre and post neurons, respectively, x_i and x_j are the membrane potentials of the two neurons, respectively.

In a chemical synapse, the presynaptic neuron releases a chemical called a neurotransmitter that sticks to receptors located in the postsynaptic cell and can affect the postsynaptic cell in a wide variety of ways. Chemical synapses can be excitatory or inhibitory, and usually they can be described as a non-linear function [20], $f(x_i, x_j) = -(x_i - V_s) \Gamma(x_j)$, where V_s is the reverse potential and set as $V_s > x_i(t)$ for any membrane potentials x_i to make all the synapses excitatory (in this paper $V_s=2$, see Fig. 1), $\Gamma(x_j) = 1/[1 + \exp\{-\lambda(x_j - \Theta_s)\}]$, whose limit form is the Heaviside step function and the value of the threshold Θ_s should be set to a value to stimulate bursting of all neurons, which pass it over (in this paper $\Theta_s = -0.25$, see Fig. 1).

Synapses can learn by themselves, which can be described by changing the weights of synapses according to some learning rules. We use a learning rule, which is a modification of the Oja concept [21]. Oja learning rule is expressed as $\Delta w_{ij} = L x_i (x_j - x_i w_{ij})$, where Δw_{ij} denotes the change in the value of the weight w_{ij} between neurons i and j , L denotes learning rate of synapses, and x_i and x_j have the same meanings as stated above. This rule can make a neural network to lose stability [22]; hence we modify the Oja rule by applying a non-linear scale-limited function $f(x) = \arctan(x)$. The modified learning rule is expressed as follows:

$$\Delta w_{ij} = L \arctan[x_i (x_j - x_i w_{ij})], \quad (2)$$

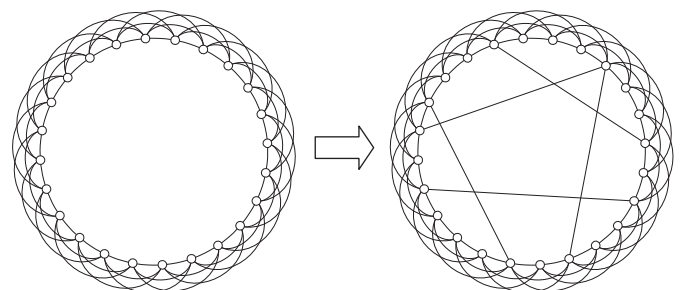


Fig. 2. From regular neuronal network (left) to NW small-world neuronal network (right).

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