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Periodic coupling strength-dependent multiple coherence resonance by time delay in Newman–Watts neuronal networks

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ABSTRACT

Recently, multiple coherence resonance induced by time delay has been observed in neuronal networks with constant coupling strength. In this paper, by employing Newman–Watts Hodgkin–Huxley neuron networks with time-periodic coupling strength, we study how the temporal coherence of spiking behavior and coherence resonance by time delay change when the frequency of periodic coupling strength is varied. It is found that delay induced coherence resonance is dependent on periodic coupling strength and increases when the frequency of periodic coupling strength increases. Periodic coupling strength can also induce multiple coherence resonance, and the coherence resonance occurs when the frequency of periodic coupling strength is approximately multiple of the spiking frequency. These results show that for periodic coupling strength time delay can more frequently optimize the temporal coherence of spiking activity, and periodic coupling strength can repetitively optimize the temporal coherence of spiking activity as well. Frequency locking may be the mechanism for multiple coherence resonance induced by periodic coupling strength. These findings imply that periodic coupling strength is more efficient for enhancing the temporal coherence of spiking activity of neuronal networks, and thus it could play a more important role in improving the time precision of information processing and transmission in neural networks.

1. Introduction

Neurons are coupled to each other via synapses and constitute neural networks, and information transmission in neural systems is fulfilled by coupled neurons and neural networks. Studies have shown that neural networks have characters of scale-free (Barabási and Albert, 1999; Eguíluz et al., 2005) and small-world (Watts and Strogatz, 1998; Newman and Watts, 1999a, 1999b; Newman, 2000) topology. Watts–Strogatz and Newman–Watts small-world networks are often studied since they can better mimic most of real networks. In Newman–Watts model, long-range random shortcuts are added between pairs of non-adjacent-vertices chosen at random, while maintaining the original edges of the underlying ring, and thus the new long-range edges increase the total number of connections from that of the original network. Since Newman–Watts topology characterizes the information transmission among neurons, it is often employed to study the firing dynamics of neuronal networks.

Neurons are noisy elements, and noise in neurons arises from many different sources, such as the quasi-random release of neurotransmitters by the synapses and random synaptic input from other neurons and the random switching of ion channels. In the past decades, stochastic resonance (SR) and coherence resonance (CR) have been extensively studied in neuronal systems. In recent years, the focus of this subject has switch to the temporal and spatial SR and CR in excitable media and neuronal networks, and many novel phenomena have been found, such as CR due to channel blocking on Newman–Watts networks of Hodgkin–Huxley (HH) neurons (Ozer et al., 2009a), spatial coherence resonance on diffusive and small-world networks of HH neurons (Sun et al., 2008) and on delayed HH neuronal networks (Wang et al., 2010a), spatial decoherence induced by small-world connectivity in excitable media (Perc, 2005), small-world connectivity enhanced noise-induced temporal and spatial order in neural media (Perc, 2007), and SR on Newman–Watts networks of HH neurons with local periodic driving (Ozer et al., 2009b).

In neural networks, information transmission delay is inherent because of both the finite speed at which action potentials propagate across neuron axons and time lapses occurring in both dendritic and synaptic processing (Kandel et al., 1991). Studies have shown that time delay and neuronal coupling have significant effects on the firing dynamics of neural networks. For instance, time delay can facilitate and improve neuronal synchronization (Dhamala et al., 2004; Rossoni et al., 2005; Burić et al., 2008) and induce various spatiotemporal patterns (Roxin et al., 2005) as well as enhance the coherence of spiral waves in noisy HH neuronal

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networks (Wang et al., 2008a). It can also induce multiple SR, CR and synchronization transitions in various neuronal networks (Wang et al., 2008b, 2009a, 2009b, 2010b, 2011; Gong et al., 2010, 2011; Hao et al., 2010, 2011a, 2011b; Gan et al., 2010). Neuronal coupling can also induce SR, CR, synchronization and firing transition in the firing activity of coupled neurons and excitable systems (Hu and Zhou, 2000; Wang et al., 2000; Zhou et al., 2001, 2003; Li and Li, 2006; Li and Lang, 2006; Li and Liu, 2006). These results show that time delay and neuronal coupling have many positive roles in the information processing and transmission in neural systems.

However, constant coupling strength has always been employed in the above studies, which is obviously far from real neural networks. It has been shown that the synapses of a neuron are plastic and neuronal coupling is always changing with time such that the neurons can adjust their firing behaviors to reach new coherent and synchronized performance. The coupling of neurons comprises electrical (gap-junction) and chemical synapses. Gap-junction coupling represents the direct information transmission between two neurons, and the coupling strength may symbolize the amount of transmitted information. Consequently, neural networks with either gap-junction or chemical synapses are plastic as well. Also, coupling strength is finite, which requires that coupling strength change nonlinearly. For simplicity, the time-varying coupling strength can be assumed to be periodic in time. Very recently, Birzu et al. have studied the effect of time-periodic coupling strength on the firing dynamics of a globally coupled array of Fitzhugh–Nagumo oscillators, and rich oscillatory and resonant behavior have been observed when time-periodic coupling strength frequency is varied (Birzu and Krischer, 2010).

In this paper, we study the temporal coherence of spiking activity in delayed Newman–Watts HH neuron networks with time-periodic coupling strength. Our goal is to investigate how time delay induced CR changes when the frequency of periodic coupling strength is varied, and how periodic coupling strength influences the temporal coherence of spiking activity and induces CR in the neuronal networks.

2. Model and equations

According to the HH neuron model, the dynamics of the membrane potential $V(t)$ can be described by

$$C\frac{dV}{dt} = -g_{\mathrm{Na}}m^3h(V-V_{\mathrm{Na}}) - g_K n^4(V-V_K) - g_L(V-V_L) + \xi(t) \tag{1a}$$

and the stochastic gating variables m, h, and n obey the following Langevin equations:

$$\dot{m} = \alpha_m(V)(1-m) - \beta_m(V)m, \tag{1b}$$

$$\dot{h} = \alpha_h(V)(1-h) - \beta_h(V)h, \tag{1c}$$

$$\dot{n} = \alpha_n(V)(1-n) - \beta_n(V)n, \tag{1d}$$

with voltage-dependent opening–closing transition rates given by

$$\alpha_m(V) = \frac{0.1(V+40)}{1-\exp[-(V+40)/10]} \tag{2a}$$

$$\beta_m(V) = 4\exp[-(V+65)/18] \tag{2b}$$

$$\alpha_h(V) = 0.07\exp[-(V+65)/20] \tag{2c}$$

$$\beta_h(V) = \frac{1}{1+\exp[-(V+35)/10]} \tag{2d}$$

$$\alpha_n(V) = \frac{0.01(V+55)}{1-\exp[-(V+55)/10]} \tag{2e}$$

$$\beta_n(V) = 0.125\exp[-(V+65/80)] \tag{2f}$$

where $C = 1\ \mu\mathrm{F/cm}^2$, $g_{\mathrm{Na}} = 120\ \mathrm{mS/cm}^2$, $g_K = 36\ \mathrm{mS/cm}^2$, and $g_L = 0.3\ \mathrm{mS/cm}^2$, $V_{\mathrm{Na}} = 50$ mV, $V_K = -77$ mV, and $V_L = -54.4$ mV. $\xi(t)$ is a Gaussian white noise with vanishing mean and autocorrelation function $\langle\xi(t)\xi(t')\rangle = D\delta(t-t')$, and $D = 0.05$ is noise intensity.

According to Newman–Watts topology (Watts and Strogatz, 1998; Newman and Watts, 1999a, 1999b; Newman, 2000), the present Newman–Watts HH neuron network starts with a regular ring comprising $N = 60$ identical neurons, with each neuron having two nearest neighbors ($k = 2$). Then links are randomly added between non-nearest vertices. In the limit case that all neurons coupled to each other, the network contains $N(N-1)/2$ edges. Using M to denote the number of added shortcuts, the fraction of the shortcuts is given by $p = M/[N(N-1)/2]$, which is used to characterize the randomness of the network topology.

The dynamics of the HH neuron networks can be written as

$$\begin{aligned} C\frac{dV_i}{dt} &= -g_{\mathrm{Na}}m_i^3h_i(V_i-V_{\mathrm{Na}}) - g_K n_i^4(V_i-V_K) - g_L(V_i-V_L) \\ &\quad + \sum_j \varepsilon_{ij}(V_j(t-\tau)-V_i) + \xi_i(t) \end{aligned} \tag{3}$$

$$\frac{dx_i}{dt} = \alpha_{x_i}(V_i)(1-x_i) - \beta_{x_i}(V_i)x_i, \quad (x = m, h, n) \tag{4}$$

where τ is time delay (in unit of ms), $\sum_j \varepsilon_{ij}[V_j(t-\tau)-V_i]$ is the coupling term, V_i is the membrane potential of the ith neuron at time t, $V_j(t-\tau)$ is the membrane potential of jth neuron at earlier time $t-\tau$, $1 \le (i, j) \le N$, N is the number of neurons, and the summation takes over all neurons; ε_{ij} is a coupling constant between the two neurons i and j, which is determined by the coupling pattern of the system and is identical for any two neurons. $\varepsilon_{ij} = \varepsilon$ if neurons i and j are connected; $\varepsilon = 0$ otherwise. Here, we employ time-periodic coupling strength (TPCS) in the form as (Birzu and Krischer, 2010):

$$\varepsilon = \varepsilon_0(1+\cos\ \omega t) \tag{5}$$

where ε_0 is the amplitude and ω is the frequency of TPCS.

Coefficient of variation λ_i is used to quantify the temporal coherence of the spiking behavior of a neuron on the network, which is defined as

$$\lambda_i = \frac{\langle T\rangle}{\sqrt{\langle T^2\rangle - \langle T\rangle^2}} \tag{6}$$

and the average of λ_i over all neurons is

$$\lambda = \frac{1}{N}\left[\sum_{i=1}^{N}\lambda_i\right] \tag{7}$$

where T is the inter-spike interval in the time series of $V_i(t)$, and $\langle T\rangle = (1/M)\sum_{k=0}^{M-1}(t_{k+1}-t_k)$ and $\langle T^2\rangle = (1/M)\sum_{k=0}^{M-1}(t_{k+1}-t_k)^2$ are the mean and mean-squared values, respectively, and M is the number of spikes. The threshold value for a spike is −20 mV. Larger λ_i or λ denotes more ordered spiking behavior.

Numerical integration of Eqs. (3)–(5) is carried out by using explicit Euler method with time step of 0.001 ms. Periodic boundary conditions are employed and the parameter values for all the neurons are identical except for distinct initial values of potential V_{i0} and the noise terms $\xi_i(t)$ for each neuron. In each calculation, the initial values of the membrane potentials of all neurons are chosen randomly.