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Coherence resonance in stimulated neuronal network

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ABSTRACT

We consider a neuronal network model where an external stimulus excites some neurons, which in turn activate other neurons in the network via synapse. We find that the regularity in macroscopic spiking activity of the whole neuronal network maximizes at a certain level of intrinsic noise. A similar resonant behavior, referred to as coherence resonance, is also observed with respect to the stimulus strength, network size, and number of stimulated neurons. The coherence is quantitatively estimated with the signal-to-noise ratio calculated from the average power spectra of the macroscopic signal and with autocorrelation time. Overall synchronization in the neuronal network also exhibits a non-monotonic dependence on the network size.

1. Introduction

As all real systems, the neural systems are noisy. Among many different sources of noise, the ones worth mentioning are quasi-random release of neurotransmitters by synapses, random synaptic input from other neurons, and random switching of ion channels. Noise plays an advantageous role in the nervous system and is needed for its good functionality in all levels of organization, starting with cells and ending with the brain. Stochastic processes in the brain may have different origins, such as, probabilistic random spontaneous neural activity and random synaptic connections [1]. Inherent brain noise plays an important advantageous role in signal detection and decision-making by preventing deadlocks, underlying important mechanisms of brain functionality and self-organization [2–4].

In recent years, the effects of noise in neural systems have attracted a lot of attention of neurophysiologists and physicists, especially due to its benefits, such as coherence and stochastic resonances [5–8,10]. In *coherence resonance* the regularity of a noisy or a chaotic system maximizes at a certain value of a random or a chaotic force. When the force is random, it is referred to as *stochastic coherence resonance* [6,7,10], while in a chaotic system it is called *deterministic coherence resonance* [11–13]. Coherence resonance can occur either in a bistable or an excitable system close to the excitation threshold. Stochastic resonance [5,8,14,15] is a particular case of coherence resonance when a periodic signal is present. It is characterized by a maximum in the signal-to-noise ratio with respect to noise or chaos intensity. Stochastic resonance is always accompanied by coherence resonance.

In a notable paper [5], Simonotto et al. showed that noise improves perception when a visual stimulus is below the perception threshold. They interpreted this result as stochastic resonance in a nervous system. Although this work stimulated further research in this direction, including the present one, there are some uncertainties in this interpretation. First of all, the perception stimulus is not periodic. Therefore, in fact they deal with coherence resonance, but not with stochastic resonance. Second, the darkness of the image background (or fog) is not noise, it is rather associated with the perception threshold. So, you may ask: Where is the noise? Noise is in the brain. We may also suggest the brain adjusts intrinsic noise to increase signal-to-noise ratio while receiving a very weak stimulus. However, this is only half of the story.

In 2003, Toral et al. [10] found noise-induced coherence resonance in a network of FitzHung–Nagumo oscillators. They showed that the network coherence maximized at a certain network size. A similar size-dependent resonance effect was previously observed in an ensemble of coupled bistable noise-driven oscillators subjected to a periodic force [8]. The authors of the above papers suggested that not only noise, but also the network size can be adjusted to enhance the sensitivity of a neural system in signal recognition. It is not yet clear how the brain adjusts network size. We may

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suppose that synaptic plasticity plays a key role in this process, or the brain adjusts a number of excited neurons or a number of autapses. Autapse-induced coherence resonance was recently demonstrated in a scale-free network of stochastic Hodgkin–Huxley neurons [9].

In this paper, we focus in studying coherence phenomenon in a network of globally coupled neural oscillators with randomly distributed coupling strengths under the influence of intrinsic noise. In particular, we investigate how noise intensity, network size, and the number of stimulated neurons affect the network regularity (coherence). As a basic model we choose the Rulkov map [16]. We should note that map-based neuron models are highly effective for numerical simulations of neural dynamics and functionality in neurobiological networks because they allow studying the interaction between individual neurons and mean field oscillations formed in large-scale networks. They can also be used for implementation of biological neuronal mechanisms responsible for signal processing of sensory information, such as visual, auditory and tactile, as well as for designing real-time synthetic neurobiological controllers for biometric robots and neuronal prosthetic devices.

Recently, the neuronal bursting activity was studied in a network of globally coupled Rulkov maps [17]. The authors of the paper investigated the network synchronization by analyzing the macroscopic signal of the whole network. Such an approach is very convenient when microscopic access to individual neurons is not possible, e.g., to simulate experiments with neural cultures grown on a multielectrode matrix. The synchronized collective bursting activity of many neurons has been shown to be associated with some pathological states, e.g., epilepsy [18] and migraine [19]. In the present work, we use the same macroscopic approach to reveal the mechanisms responsible for the regularity of the collective bursting dynamics or the network coherence.

The coherence can be estimated using different approaches. The common measures for the coherence used in previous papers were the characteristic correlation time, normalized fluctuation of phase duration (or jitter) [6,10] and signal-to-noise ratio (SNR) evaluated from power spectra [7,15,21]. Other measures, such as bifurcation diagrams of peak amplitude and inter-spike intervals (ISI), normalized standard deviation (NSD) of peak amplitude (amplitude coherence) and NSD of ISI (time coherence), and Lyapunov exponents were also used [12,13]. In this paper we will apply different kinds of analysis to measure the network coherence, in particular, time series analysis, spectral analysis and correlation analysis. We will also study synchronization in order to know whether or not it is related to the coherence.

2. The model

Each Rulkov neuron [16] in noisy environment is described by the following system of equations

$$\begin{aligned} x_{n+1} &= f(x_n, x_{n-1}, y_n + \beta_n), \\ y_{n+1} &= y_n - \mu(x_n + 1) + \mu\sigma + \mu\sigma_n + \mu A^{\xi}\xi_n, \end{aligned} \tag{1}$$

where x and y are fast and slow variables associated with membrane potential and gating variables, respectively, α, σ and $\mu \in (0, 1]$ are parameters which regulate the system dynamics, ξ is Gaussian noise with zero mean and unity standard deviation, A^{ξ} is the noise amplitude, and f is a piecewise function defined as

$$f(x_n, x_{n-1}, y_n) = \begin{cases} \alpha/(1-x_n) + y_n, & \text{if } x_n \le 0, \\ \alpha + y_n, & \text{if } 0 < x_n < \alpha + y_n \text{ and } x_{n-1} \le 0, \\ -1, & \text{if } x_n \ge \alpha + y_n \text{ or } x_{n-1} > 0, \end{cases} \tag{2}$$

constructed in a way to reproduce different regimes of neuron-like activity, such as spiking, bursting and silent regimes. Here, β_n and σ_n are parameters related to external stimuli and defined as

$$\begin{aligned} \beta_n &= \beta^e I_n^{ext} + \beta^{syn} I_n^{syn}, \\ \sigma_n &= \sigma^e I_n^{ext} + \sigma^{syn} I_n^{syn}, \end{aligned} \tag{3}$$

where β^e and σ^e are coefficients used to balance the effect of external current I_n^{ext} defined as

$$I_n^{exp} = \begin{cases} 0, & n < t_s, \\ A, & n \ge t_s, \end{cases} \tag{4}$$

β^{syn} and σ^{syn} are coefficients of chemical synaptic coupling [20], and I_n^{syn} is a synaptic current given as

$$I_{n+1}^{syn} = \gamma I_n^{syn} - g_{syn} * \begin{cases} (x_n^{post} - x_{rp})/(1 + e^{-k(x_n^{post} - \theta)}), & \text{when } x_n^{pre} \ge \alpha + y_n^{pre} + \beta_n^{pre}, \\ 0, & \text{otherwise}, \end{cases} \tag{5}$$

where $g_{syn} \ge 0$ is the strength of synaptic coupling, $\theta = -1.55$ and $k = 50$ are synaptic parameters which stand for the synaptic threshold behavior. The super indices *pre* and *post* refer, respectively, to the presynaptic and postsynaptic variables, $\gamma \in [0, 1]$ is the synaptic relaxation time defining a portion of synaptic current preserved in the next iteration, and x_{rp} is a reversal potential determining the type of synapse, inhibitory or excitatory. The parameter values are chosen so that uncoupled neurons are in a resting state, namely, $\alpha = 3.65$, $\sigma = 0.06$ and $\mu = 0.0005$. We also assume $\beta^e = 0.133$, $\sigma^e = 1.0$, $\beta^{syn} = 0.1$, $\sigma^{syn} = 0.5$ and $x_{rp} = 0$.

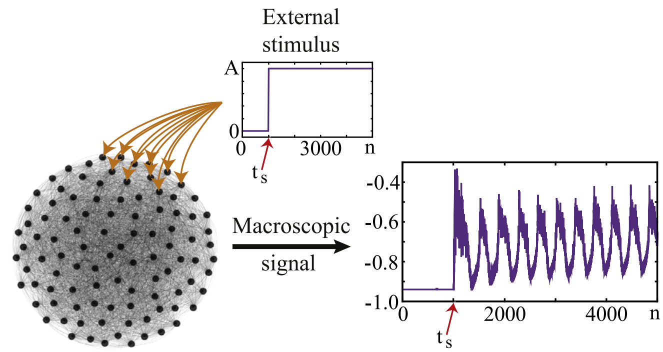

Fig. 1. Research design. The external stimulus with amplitude A is applied at time t_s to excite Na neurons in the network of N neurons. The macroscopic signal is the time series averaged over all neurons in the network.

The research design is shown in Fig. 1. We consider a network of N globally coupled neurons with random coupling strength $g_{syn} \in [0, 1]$ and relaxation time $\gamma \in [0, 0.5]$.

Without external stimulation and in the absence of noise, all neurons are in a silence regime. The external current in the form of a rectangular pulse with amplitude A is applied to Na neurons at time t_s. This stimulation excites Na neurons, which in turn excite other neurons in the network. Since the coupling strength is random, some of the neurons fire in a periodic spiking regime, some in an irregular bursting regime, and some remain in a silent state. Here, we are interested in macroscopic dynamics representing the global network behavior. The macroscopic signal shown in the right-hand panel of Fig. 1 exhibits the time series of the fast variable x averaged over all neurons in the network.

3. The analysis

In this section we will show how regularity of the macroscopic signal depends on the number of stimulated neurons Na, the network size N, the amplitude of external stimulus A, and the amplitude of noise A^{ξ}. We will start with the time series analysis, and