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Collective Stochastic Resonance: A Mechanism to Enhance Stimuli in Neural Networks

Marinho A. Lopes[1,†], Alexander V. Goltsev[1,2] and Jose F.F. Mendes[1]

[1] *Departamento de Fisica, Universidade de Aveiro, 3810-193 Aveiro, Portugal*

[2] *A. F. Ioffe Physico-Technical Institue, 194021 St. Petersburg, Russia*

Abstract. Using a stochastic model of neural networks, we investigate analytically and numerically response of neural networks on weak time dependent stimuli in the presence of noise. We propose a new mechanism of stochastic resonance, so called "collective stochastic resonance". It occurs in neural networks which undergo a transition from a state with short-range spatio-temporal correlations between neurons to a state with network oscillations. We find that dynamical stochastic resonance emerges as the precursor of global oscillations. It increases the output signal-to-noise ratio and improves the recognition of weak sensory stimuli. We show that a modular organization of neural networks can improve the reliability of detection of weak signals.

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† **Corresponding author:** mal@ua.pt
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1. Introduction

The stochastic resonance (SR) is a phenomenon which seems to contradict the common sense, because it is a process which describes an amplification and an optimization of detection of weak signals by noise [1]. The nature found in SR a method to use noise for its own benefit. Experimental evidences for SR in biological sensory systems were found in crayfish mechanoreceptors and paddlefish [2].

SR has also been observed in neurobiological experiments in mammalian brain [3]. Several models have been proposed to explain the mechanism of SR which are based on non-linear dynamics of single neurons [3]. However little attention has been paid to experimental evidences which show that SR may also be related to collective behavior of neurons and brain waves [4].

In the present paper we study the response of neural networks on time dependent stimuli in the presence of noise and demonstrate that noise plays a positive role in dynamics of neural networks.

2. Model

In brain, neurons form a complex network which has properties of a so called "small world" [6]. Many of structural properties of neural networks are similar to properties of other complex networks which were widely studied in the past decade in physics, social science and biology [7, 8]. In the present paper, we study a model of stochastic dynamics of neural networks proposed in [5]. This model consists of two neural populations, excitatory and inhibitory neurons on a directed complex network (the Erdős-Rényi network). We take into account noise which plays an important role in brain functioning [9, 10, 11]. Dynamical behavior of neural networks under consideration is described by the fractions of excitatory and inhibitory neurons which are active at time t. These parameters are represented by functions $\rho_e(t)$ and $\rho_i(t)$, respectively. A neuron becomes active and fires a spike train if the total input from active presynaptic neurons is at least a threshold. It is important to note that active excitatory neurons give a positive input in contrast to a negative input from active inhibitory neurons. Noise also can activate neurons. Basing on experimental investigations [10], we assume that activation and deactivation of neurons are stochastic processes. The functions $\rho_e(t)$ and $\rho_i(t)$ are determined by two rate nonlinear equations which describe stochastic dynamics of neural networks at the presence of noise [5]. Solving these equations, we find that the neural network demonstrate three different kinds of temporal behavior of neural activity: (I) the exponential relaxation to a steady state; (II) decaying oscillations; and (III) stable network oscillations.

3. Dynamical and Threshold Stochastic Resonance

In order to study how stimuli are processed by a neural network, first we analyze a response of neural networks to a time-dependent signal. There are two equivalent ways to stimulate a neural network. The first way is to assume that a stimulus is encoded in a parameter F which characterizes the level of noise in the system. The second way is to introduce sensory neurons which deliver an external signal to neurons in the neural network.

We consider the case $F(t) = F + A\sin(\omega t)$ where the second term is a weak periodic signal with a frequency ω and an amplitude $A \ll F$. This weak periodic stimulation results in a periodic modulation of neural activity $\rho_a(t) = \rho_a + B_a \sin(\omega t + \varphi)$ of excitatory ($a = e$) and inhibitory ($a = i$) neurons, respectively. We find that the signal-to-noise ratio (SNR) defined as $\eta \equiv |B_e|^2/|A_e|^2$ is proportional to $1/(\gamma_r^2 + (\gamma_i - \omega)^2)$, where $\gamma_r = Re(\gamma)$ and $\gamma_i = Im(\gamma)$ are the real and imaginary parts of a complex rate which characterizes the relaxation of neural activity to a steady state. This result shows that if γ_r tends to zero and $\omega \to \gamma_i$, then this response is strongly amplified. The response diverges at a critical value of the noise level F_c when the neural network is in a critical state on the boundary between the regions with damping and stable network oscillations. On this boundary the network undergoes the dynamical phase transition from a state with short-range spatio-temporal correlations between neurons to a state with global network oscillations. The frequency dependence of the SNR η is represented in Fig. 1 at different levels of noise. One can see that there is an optimal level of noise at which η reaches a maximum. This kind of dependence describes so called *dynamical stochastic resonance* [11], i.e., an amplification of the signal-to-noise ratio by noise.

Let us study the problem of recognition of weak signals by the neural network in the presence of noise and introduce sensory neurons connected to excitatory neurons. We consider the case when at a given level of noise generated, for example, by the Gaussian process, the neural network is in a state with damping neural oscillations close to the boundary with stable global oscillations. We add a weak subthreshold sensory signal in the form of short pulses which alone can not generate oscillations. The amplitude of short pulses is about 2.4 times smaller than the average level of noise. We obtain that despite the response of the neural network to this signal+noise input is stochastic, the network "recognizes" these pulses with a certain probability. This phenomenon is so called *threshold stochastic resonance* (tSR) [12].

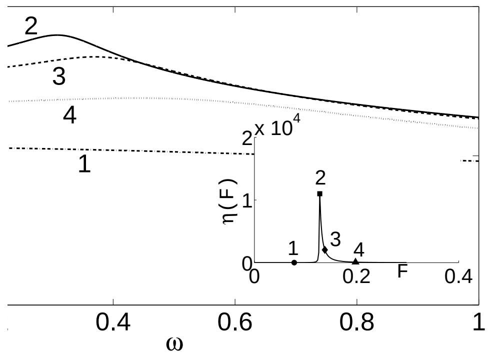

Figure 1: Signal-to-noise ratio η versus frequency ω of a periodic stimulus at different levels of noise F labeled by the indices 1,2,3, and 4. These levels are shown in the inset by dots. The inset shows a dependence of η versus F at the frequency $\omega = \gamma_i$ corresponding to the maximum of η.

4. Transmission of a Message

Let us consider a case when a sensory signal carries information. For simplicity, we encode information as a sequence of pulses in a sensory signal. In order to improve recognition of a message, we use the following approach. First, let us split a neural network into n modules (or subpopulations) which are synaptically uncoupled. One should note that development of modular organization as a result of evolutionary process of the brain is topic of modern investigations [13]. Second, we assume that sensory neurons provide divergent input to neurons in these modules. Such divergence of sensory input was observed, for example, in auditory inner hair cells [14]. Thus, these modules carry the same signal and each subpopulation is affected by independent sources of noise. Then, n signals arriving simultaneously from all modules are summed in an integrator and we obtain an averaged signal. Averaging is the other key principle which the central nervous system uses to reduce noise [10]. If there are n modules and each module misses in average x pulses out of y, then the probability that all n responses contain an error is equal to $(x/y)^n$. If we want to detect the message with the probability 99%, then the necessary number n modules can be found from the condition $(x/y)^n = 0.01$ (see, for example, in Ref. [15]). For parameters used in our numerical calculations, the probability of the error is about 2/7, i.e., two pulses from seven on average may be missed. In this case, the necessary number of modules is $n = 4$.

5. Conclusions

We propose a new mechanism of stochastic resonance in neural networks, so called "collective stochastic resonance". It emerges due to collective behavior of excitatory and inhibitory neurons. We found that collective stochastic resonance occurs in neural networks which undergo a phase transition from a state with short-range spatio-temporal correlations between neurons to a state with network oscillations. This dynamical phase transition is a collective phenomenon driven by interactions between excitatory and inhibitory neurons. It manifests itself in enhancement of response of neural networks on periodic stimuli in a certain range of frequencies. We gave evidences that if neural networks are close to the region with network oscillations then due to threshold SR the recognition of weak sensory signals may be improved at the presence of noise. Modular organization of neural networks benefits this recognition.

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