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External stimulus classification by Hodgkin-Huxley neural network

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ABSTRACT

We propose to use the chimera-like state for stimulus classification in a spiking neural network of bistable HH neurons. As a stimulus, we use an external pulsed current applied to the network. Additive noise makes the neurons nonidentical so that the external pulse switches only a part of the neurons from the resting to the oscillatory state depending on the pulse amplitude. For classification, we use the neural network and two output neurons. The network is trained on two external pulses with different amplitudes to adjust coupling strengths between neurons in the main network and output neurons. We investigate influence of inhibitory coupling between output neurons on classification of input signal with different amplitudes.

Keywords: Classification, Hodgkin-Huxley neuron, neural network, complex network, small-world

1. INTRODUCTION

The dynamics of complex networks has attracted much attention in recent years.[1–6] Especially, the networks of spiking neurons or neuron-like elements take a significant part of this area[7–13] along with neural networks of human brain.[14–17] There are many interesting phenomena which have been found in such networks and which are still investigating. Especially, chimera state has been elaborately investigated during the past decade in a wide range of systems.[18–23] It was firstly observed in nonlocally coupled identical phase oscillators as the coexisting coherence and incoherence patterns by Kuramoto and Battogtokh.[24] Later, chimera state has been observed in leaky integrate-and-fire neurons with excitatory coupling,[25] as well as in networks of FitzHugh-Nagumo[26] and Hindmarsh-Rose neuronal oscillatory systems.[27] Chimera-like states have also been analyzed for non-locally coupled Hodgkin–Huxley oscillators[28] and in many other different neuronal network models.

One of the important questions here is a control and practical application of chimeras in neuronal networks. Earlier, the authors of[29] described pinning control of coherent and incoherent domains in chimera patterns for ensembles of nonlocally coupled FitzHugh-Nagumo systems. Also a control by an external current pulse was presented in the network of Hodgkin-Huxley neurons.[30] One of the possible application of chimera state is using it in spiking neural network (SNN) classifier.

It is believed that the SNN-based computations have great potential[31,32] and, theoretically, can reach enormous computational efficiency like real brain circuits.[33] Nowadays many studies attempt to use SNNs for practical applications, for example, for speech recognition,[34] audio-visual pattern recognition,[35,36] robot controlling,[37] etc. The use of spiking neurons as classifiers in pattern recognition problems of visual information recorded from a silicon retina,[38] and in simulation of sound information processing in the auditory cortex[39,40] has been reported.

In this paper, we propose a spiking neural network that can be used for classification of external signal. As a model of neurons we use Hodgkin-Huxley neurons as one of the most realistic one. Work of the classifier based on the activation of a different number of neurons depending on the external current amplitude.[30] We train it for 2 external current pulses with different amplitudes by adaptation of the couplings between neurons of the

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main network and 2 output neurons. We investigate influence of inhibitory coupling between output neurons on classification of input signal with different amplitudes. We show that there is a threshold value of the pulse's amplitude before which the network classifies the input signal as the first type and as the second type after it.

2. NUMERICAL MODEL

We consider the network of $N = 100$ Hodgkin-Huxley neurons. The time evolution of the transmembrane potential of the HH neurons is given by[41]

$$C_m \frac{dV_i}{dt} = -g_{Na}^{max} m_i^3 h_i (V_i - V_{Na}) - g_K^{max} n_i^4 (V_i - V_K) - \\ - g_L^{max}(V_i - V_L) + I_i^{ex} + I_i^{syn} \tag{1}$$

where $C_m = 1\mu F/cm^3$ is the capacity of cell membrane, I_i^{ex} is an external bias current injected into a neuron in the network, V_i is the membrane potential of i-th neuron, $i = 1,...,N$, $g_{Na}^{max} = 120mS/cm^2$, $g_K^{max} = 36mS/cm^2$ and $g_L^{max} = 0.3mS/cm^2$ receptively denote the maximal sodium, potassium and leakage conductance when all ion channels are open. $V_{Na} = 50mV$, $V_K = -77mV$ and $V_L = -54.4mV$ are the reversal potentials for sodium, potassium and leak channels respectively. m, n and h represent the mean ratios of the open gates of the specific ion channels. n^4 and m^3h are the mean portions of the open potassium and sodium ion channels within a membrane patch. The dynamics of gating variables $(x = m, n, h)$ are given:

$$\frac{dx_i}{dt} = \alpha_{x_i}(V_i)(1 - x_i) - \beta_{x_i}(V_i)x_i, \qquad x = m, n, h \tag{2}$$

$\alpha_x(V)$ and $\beta_x(V)$ are rate functions, described by[42]

$$\alpha_m(V) = \frac{0.1(25 - V)}{\exp[(25 - V)/10] - 1} \tag{3}$$

$$\beta_m(V) = 4\exp(-V/18) \tag{4}$$

$$\alpha_h(V) = 0.07\exp(-V/20) \tag{5}$$

$$\beta_h(V) = \frac{1}{1 + \exp[(30 - V)/10]} \tag{6}$$

$$\alpha_n(V) = \frac{0.01(10 - V)}{\exp[(10 - V)/10] - 1} \tag{7}$$

$$\beta_n(V) = 0.125\exp(-V/80) \tag{8}$$

I_i^{syn} is the total synaptic current received by neuron i. We consider coupling via chemical synapses. The synaptic current takes the form[43]

$$I_i^{syn} = \sum_{j \in neigh(i)} g_c \alpha(t - t_0^j)(E_{rev} - V_i) \tag{9}$$

where the alpha function $\alpha(t)$ describes the temporal evolution of the synaptic conductance, g_c is the maximal conductance of the synaptic channel and t_0^j is the time at which presynaptic neuron j fires. We suppose $\alpha(t) = \mathrm{e}^{-t/\tau_{syn}}\Theta(t)$, there $\Theta(t)$ is the Heaviside step function and $\tau_{syn} = 3ms$. The initial conditions of all neurons correspond to the oscillatory basin of attraction of individual neuron.

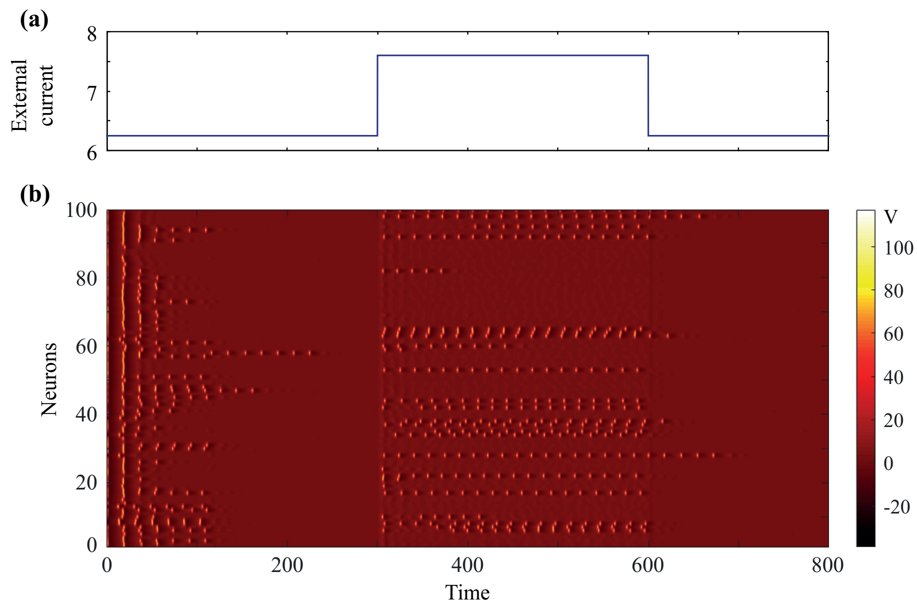

Figure 1. (a) Time series of the external current and (b) time-space plot of the membrane potential of all neurons from the main network N for $I_p^e = 1.35$ μA/cm^2.

3. RESULTS

We consider the classifier consisting of the main network of $N = 100$ HH neurons and $N^{out} = 2$ output neurons. We apply a short pulse of external current I^e as an input signal to the main network and one of the output neurons should react on it. In order to achieve it, we use the results from.[30] It has been shown that different groups of neurons can be switched from the resting state to the active one by a short pulse of external current. Moreover, network topology plays a crucial role because node stability depends on its degree. Due to scale-free topology characterized by the presence of nodes with extremely high degree we use this topology in the classifier. The adjacency matrix for the SF network is generated using the Barabási-Albert algorithm,[44] which creates a graph of $N = 100$ nodes having $m = 5$ edges each.

As we apply a short pulse of external current I^e to N neurons. It is modeled by a boxcar function as

$$\widetilde{I}^e(t) = I_0^e + I_p^e[H(t - t_0) - H(t - t_0 - \Delta t)], \tag{10}$$

where I_0^e is the amplitude of the constant current, I_p^e is the amplitude of the external pulse, $H(\bullet)$ is the Heaviside step-function, $t_0 = 300$ ms is the moment of time when the pulse is applied, and $\Delta t = 300$ ms is the time period of the pulse. We choose $I_0^e = 6.25$ μA/cm^2 corresponding to the resting state of HH neuron's dynamics.

Based on the results from[30] we choose coupling strength between neurons inside the main network $g_c^m = 0.02$. Initially, there are no couplings between the main network and the output neurons, so $g_c^{in} = 0$. Then, we train the network by adapting these couplings. We apply the external pulse with a certain amplitude and want to achieve activation of one neuron during the pulse while the second one should be inactive. We apply the external pulse with $I_p^e = 1.3$ μA/cm^2. Figure 1 illustrates how the main network reacts on the external pulse. Initially, all neurons generate one or more spikes depending on the initial conditions. Then, during the transient process from 0 to 300 ms all of them go to the resting state according to the chosen value of the constant current $I_0^e = 6.25$ μA/cm^2. Then, at $t = 300$ ms the external stimulus is applied. It induces some neurons to become active, at that number of such neurons depends on the pulse amplitude: higher I_p^e activates more neurons.[30] During the pulse some neurons can return to the resting state, the oscillations of some active ones can be suddenly terminated, but most of them generate spikes the most part of the pulse period. At $t = 600$ ms the pulse stops applying on the network, and most of the neurons being active during the pulse stops generating spike immediately, while a small number of them continue spike's generation for a while but at the end, they return to the resting state.

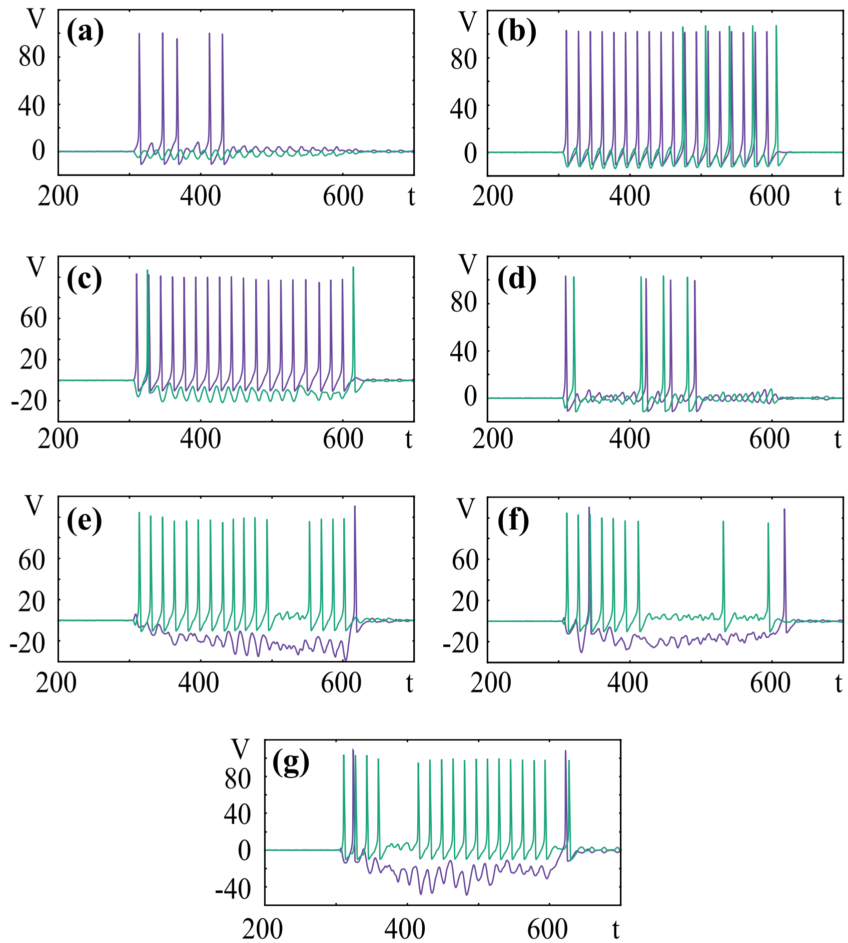

Figure 2. Time dependencies of the membrane potential of the first (blue line) and the second (red line) output neurons for $I_p^e = 1.2$ (a), 1.25 (b), 1.3 (c), 1.35 (d), 1.4 (e), 1.45 (f), 1.5 (g). $g_c^{out} = 0$.

Firstly, we consider a classifier without inhibitory coupling between output neurons, so $g_c^{out} = 0$. We train our network in such a way, so the first output neuron activates for the pulse with amplitude $I_p^e = 1.3$ μA/cm^2, and the second one activates for $I_p^e = 1.4$ μA/cm^2. Then, we investigate how the network responds to different external pulse amplitudes.

For $I_p^e = 1.2$ μA/cm^2 only the first output neurons is active (Fig. 2(a)). Increasing the pulse amplitude leads to the activation of the second one. Fig. 2(b) illustrates the dynamics of output neurons for $I_p^e = 1.25$ μA/cm^2. One can see that the first neuron generates 18 spikes during the whole pulse applying while the second one generates only 5 spikes during the second half of the pulse. As we have trained the network for $I_p^e = 1.3$ and 1.4 μA/cm^2, $I_p^e = 1.35$ is a middle point, and for this value both output neurons generate equal number of spikes (Fig. 2(d)). This case corresponds to the full uncertainty and the classifier cannot make a decision. Further increasing of the pulse amplitude leads to the reverse situation when the second neuron generates more spikes than the first one. But for $I_p^e > 1.44$ the first output neuron generate a few spikes(Figs. 2(f,g)).

Then, we consider a classifier with inhibitory couplings between output neurons with different coupling strengths (Fig. 3). One can see that adding inhibitory coupling between output neurons leads to increasing the number of spikes generated by them. For strong coupling between output neurons ($g_c^{out} = 0.4$) both of them continues to be active even after the pulse stops applying (Fig. 3(e)).

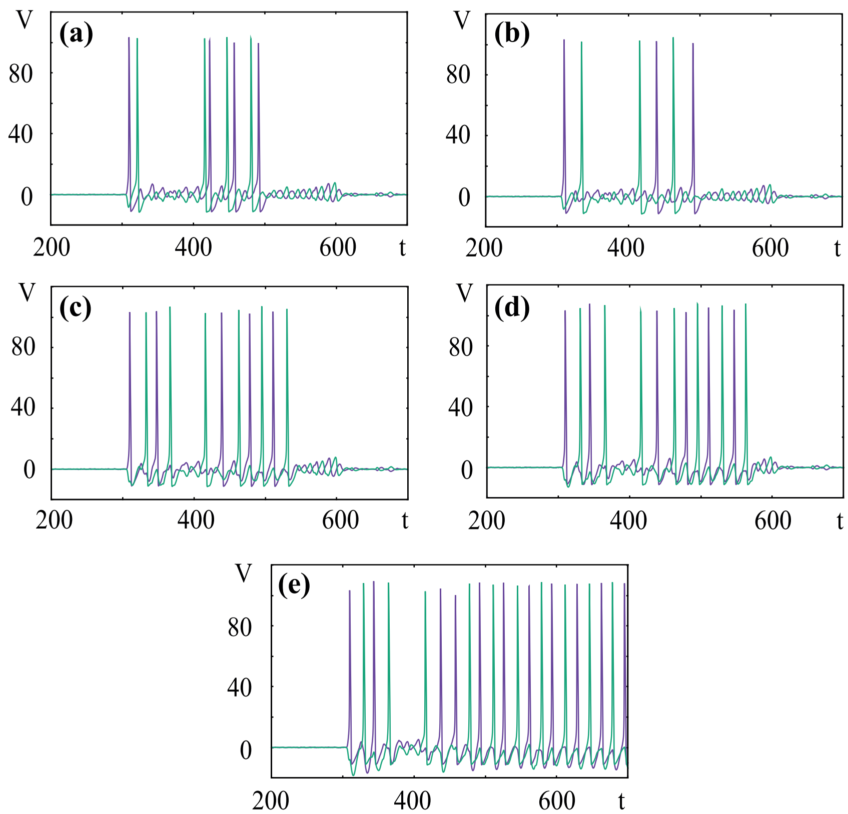

Figure 3. Time dependencies of the membrane potential of the first (blue line) and the second (red line) output neurons for $g_c^{out} = 0$ (a), 0.1 (b), 0.2 (c), 0.3 (d), 0.4 (e). $I_p^e = 1.35$.

4. CONCLUSION

We have proposed a classifier consisting of Hodgkin-Huxley neurons. It is based on the activation of a different number of neurons depending on the external current amplitude. We have considered the classifier consisting of the main network of $N = 100$ HH neurons and 2 output neurons. We have trained it for 2 external current pulses with different amplitudes by adaptation of the couplings between neurons of the main network and the output neurons: we increased the coupling strength of i-th neuron with one output neuron and decreased with another one every time when i-th neuron generate spike during the pulse applying.

We have considered two variations of the classifier's structure: with the presence or without inhibitory coupling between output neurons. We have investigated how the network responds to different external pulse amplitudes. We have shown that there is a threshold value of the pulse's amplitude before which the network classifies the input signal as the first type and as the second type after it. Adding inhibitory coupling between output neurons leads to increasing the number of spikes generated by them.

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