Classification of external signal by spiking neural network of bistable Hodgkin-Huxley neurons

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***Abstract*—We propose a classifier consisting of Hodgkin-Huxley neurons based on the activation of a different number of neurons depending on the external current amplitude. We consider a network with 2 output neurons and train the classifier for 2 external current pulses with different amplitudes by adaptation of the couplings between neurons of the main network and the output neurons.**

***Keywords*—Neural network, Hodgkin-Huxley model, Classification, Spiking neural network**

I. Introduction

Nowadays, artificial neural networks (ANN) are widely used in practical applications. One of the important applications is the use of ANN in the classification of EEG patterns [1-3]. ANNs based on artificial neurons are widely used in approximation, classification, and clustering problems. They have many advantages like high speed, efficiency, application to different data sets, ability to be imposed in any applications. That determines their wide distribution.

However, artificial neurons used in ANNs cannot reproduce real neuron's dynamics. So, using ANNs cannot help in the investigation of the processes occurring in a neural network during processing and classification of the data. And researchers need to use spiking neural networks (SNNs) for these purposes [4].

Spiking neural networks are also used for simulation of different phenomena in neuroscience [5,6], and investigation of neural activity is commonly used for brain activity studying [7-13]. The numerical simulation is important in many areas of science [14-23], including neuroscience [24].

In this paper, we propose a classifier consisting of Hodgkin-Huxley neurons based on the activation of a different number of neurons depending on the external current amplitude. We consider a network with 2 output neurons and train the classifier for 2 external current pulses with different amplitudes by adaptation of the couplings between neurons of the main network and the output neurons.

II. Model

As a model of a neuron, we consider a Hodgkin-Huxley model. The time evolution of the transmembrane potential of each HH neuron can be described by the following differential equations [25]

$$C_m \frac{dV}{dt} = -g_{\mathrm{Na}} m^3 h (V - V_{\mathrm{Na}}) - g_{\mathrm{K}} n^4 (V - V_{\mathrm{K}}) - g_{\mathrm{L}}(V - V_{\mathrm{L}}) + I^{\mathrm{ex}} + I^{\mathrm{syn}} \quad (1)$$

where $C_m = 1\mu F/cm^3$ is the capacity of cell membrane, I^{ex} is an external bias current injected into a neuron, V is the membrane potential of a neuron, $g_{\mathrm{Na}} = 120\ mS/cm^2$, $g_{\mathrm{K}} = 136\ mS/cm^2$ and $g_{\mathrm{L}} = 0.3\ mS/cm^2$ receptively denote the maximal sodium, potassium and leakage conductance when all ion channels are open. $V_{\mathrm{Na}} = 50\ mV$, $V_{\mathrm{K}} = -77\ mV$ and $V_{\mathrm{L}} = -54.4\ mV$ 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 ($x = m,n,h$) depending on rate functions $\alpha_x(V)$ and $\beta_x(V)$ are given:

$$\frac{dx}{dt} = \alpha_x(V)(1-x) - \beta_x(V)x + \xi_x(t), \qquad x = m,n,h \quad (2)$$

$\xi_x(t)$ is independent zero mean Gaussian white noise sources.

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

$$I_i^{\mathrm{syn}} = \sum_{j\in \mathrm{neight}(i)} g_c e^{-(t-t_0^j)/\tau_{\mathrm{syn}}} (E_{\mathrm{rev}} - V_i) \quad (3)$$

where the alpha function $\alpha(t)$ describes the temporal evolution of the synaptic conductance, g_c is the maximal conductance of the synaptic channel, t_0^j is the time at which presynaptic neuron j fires, $\tau_{\mathrm{syn}} = 3$ ms.

III. Results

We consider the classifier consisting of the main network of $N = 100$ HH neurons and $N^{\mathrm{out}} = 2$ output neurons (see Fig 1). 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. To achieve it, we use the results from [26]. 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

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generated using the Barabasi-Albert algorithm [27], which creates a graph of $N = 100$ nodes having $m = 5$ edges each.

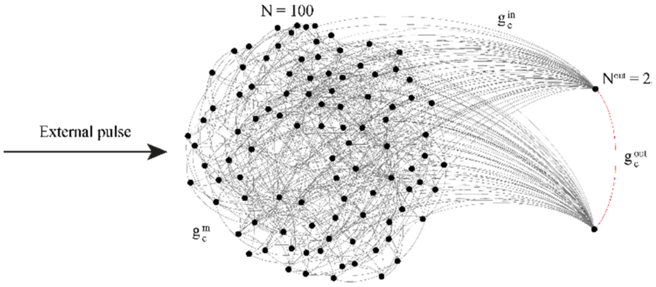

Fig. 1. Model of the classifier. An external pulse is applied to the main network consisting of $N = 100$ Hodgkin-Huxley neurons connected to each other by scale-free topology with coupling strength g_c^m. All of them are unidirectionally coupled with 2 output neurons with coupling strength g_c^{in} which initially equals 0 but changes during the adaptation process. Output neurons either uncoupled or coupled to each other by inhibitory couplings with coupling strength g_c^{out}.

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

$$\tilde{I}^e(t) = I_0^e + I_p^e[H(t - t_0) - H(t - t_0 - \Delta t)] \qquad (4)$$

where I_0^e is the amplitude of the constant current, I_p^e is the amplitude of the external pulse, $H(*)$ 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 [26] 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 firstly apply the external pulse with $I_p^e = 1.3$ μA/cm^2 and increase the coupling strength of each i-th neuron from the main network with the first output neuron and at the same time decrease g_c^{in} with the second one every time when i-th neuron generate spike. Then we do a reverse adaptation for another pulse amplitude $I_p^e = 1.4$ μA/cm^2: we increase the coupling strength with the second output neuron and decrease with the first one. Some neurons could be activated during only one of the pulses, whereas others activate during both of them, and there is a third group of neurons which doesn't activate at all. Eventually, such adaptation should lead us to the situation when only one output neuron activates for different external pulses.

Figure 2 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 [26]. 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.

IV. Conclution

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 generates spike during the pulse applying.

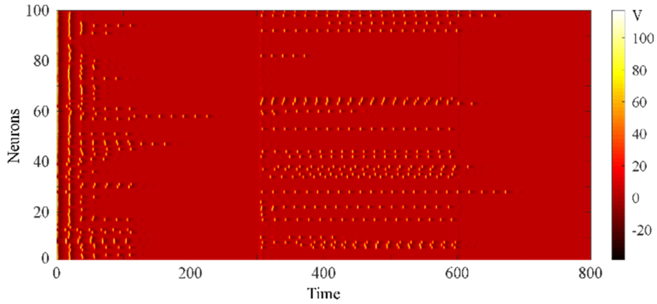

Fig. 2. Time-space plot of the membrane potential of all neurons from the main network N for $I_p^e = 1.35$ μA/cm^2.

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