

Chimera-like state in ensemble of bistable neurons

Andrey Andreev

Neuroscience and Cognitive Technology Laboratory,
Center for Technologies in Robotics and
Mechatronics Components
Innopolis University
Innopolis, Russia
a.andreev@innopolis.ru

Natalija Alexandrova

Faculty of Information Technologies
Saratov State University
Saratov, Russia
aleksandrovan@bk.ru

Nikita Frolov

Neuroscience and Cognitive Technology Laboratory,
Center for Technologies in Robotics and
Mechatronics Components
Innopolis University
Innopolis, Russia
n.frolov@innopolis.ru

Marija Chaban

Faculty of Information Technologies
Saratov State University
Saratov, Russia
64chabanma@gmail.com

Abstract—We investigate the nonlinear dynamics of a neural network. As a model of a neuron, we use Hodgkin-Huxley mathematical model. We choose the neuron’s parameters corresponding to a bistable region in which both fixed point and limit cycle are coexisting. We discover that depending on external current and coupling strength we can achieve a chimera-like state when one part of the neurons is in the resting state, while the other one is in the oscillatory regime in a certain area of coupling strength and external current amplitude.

Index Terms—Complex network, Hodgkin-Huxley neuron, neural network, chimera-like state.

I. 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]–[9]. The interest in neural networks is due it helps to make a contribution to a better understanding of brain functionality, that also is of a grate interest [10]–[15].

Collective dynamics in a neuronal network is usually considered by taking into account that every neuron in the network is monostable, i.e., it has a single stable trajectory [16]. However, according to Keener and Sneyd [17], the Hodgkin-Huxley (HH) model exhibits bistability in a narrow range of control parameters near the excitation threshold. The bistability regime in oscillatory systems as known to be of special interest due to a variety of hidden unexpected phenomena.

We investigate the nonlinear dynamics of a networks of Hodgkin-Huxley neurons for the parameters’ values corresponding to a bistable region in which both fixed point and limit cycle are coexisting. We discover a phenomenon when one part of the neurons are in the resting state, while the other one is in the oscillatory regime in a certain area of coupling strength and external current amplitude.

This work was supported by the Russian Foundation for Basic Research (Grant 19-52-45026) and the President Program (Project NSH-2594.2020.2).

II. 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 [18]

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

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, $i = 1, \dots, N$, $g_{Na}^{max} = 120mS/cm^2$, $g_K^{max} = 36mS/cm^2$ 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:

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

$\alpha_x(V)$ and $\beta_x(V)$ are rate functions, described in [19].

I_i^{syn} is the total synaptic current received by neuron i . We consider coupling via chemical synapses. The synaptic current takes the form [20]

$$I_i^{syn} = \sum_{j \in \text{neigh}(i)} g_c \alpha(t - t_0^j) (E_{rev} - V_i) \quad (3)$$

where the alpha function $\alpha(t)$ describes the temporal evolution of the synaptic conductance, g_c is the maximal conductance of the synaptic channel and t_0^j is the time at which presynaptic neuron j fires. We suppose $\alpha(t) = e^{-t/\tau_{syn}} \Theta(t)$, 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.

III. RESULTS

We investigate the dynamics of network with scale-free topology and analyze how the number of active neurons depends on both external current and coupling strength. By active neurons we mean the ones generating spikes. $I^e = 6.24$ is the threshold value for a single neuron and for current amplitudes lower than that value a neuron can be only in a “silent” regime. On the other hand for big values of external current ($I^e > 8.0$) all neurons are in oscillatory regime independently on coupling strength. Between these two threshold values of I^e networks dynamics depends on g_c .

We find a specific regime in which one part of neurons is in the resting state while another one generates spikes. We called it chimera-like state. The situation when in a complex network one part of the elements is in the resting state while another one generates spikes is of interest. And it is not so clear why the system behaves this way, because all connections in the network are excitatory, and at the first blush excitatory synapses shouldn't suppress neuron oscillations and external current is above the threshold.

It is known that dynamics of one bistable Hodgkin-Huxley neuron can be switched from oscillatory regime to resting one by short pulse of external current. In that case excitatory synapses can be represented as such pulse. So, in the network of bistable Hodgkin-Huxley neurons they can switch the dynamics of each other and as a result we observe the chimera-like state when we have two parts of neurons with different dynamics.

The excitatory synapses with the big enough amplitude can switch the neuron dynamics from initially being oscillatory to the resting one. So if all neurons in the network oscillate initially, the dynamics of the neurons with a high number of input connections can be easily switched to the resting one, while other ones having a small number of connections continue to generate spikes.

IV. CONCLUSION

We have investigated the nonlinear dynamics of a neural network. As a model of a neuron, we used the Hodgkin-Huxley mathematical model. We have chosen the neuron's parameters corresponding to a bistable region in which both fixed point and limit cycle are coexisting. We have discovered that depending on external current and coupling strength we can achieve a chimera-like state when one part of the neurons is in the resting state, while the other one is in the oscillatory regime in a certain area of coupling strength and external current amplitude.

ACKNOWLEDGMENT

The authors thank Alexander Hramov and Alexander Pisarchik for useful discussions. This work was supported by the Russian Foundation for Basic Research (Grant 19-52-45026) and the President Program (Project NSH-2594.2020.2).

REFERENCES

- [1] S. Boccaletti, G. Bianconi, R. Criado, C. I. Del Genio, J. Gómez-Gardeñes, M. Romance, I. Sendina-Nadal, Z. Wang, and M. Zanin, “The structure and dynamics of multilayer networks,” *Physics Reports*, vol. 544, no. 1, pp. 1–122, 2014.
- [2] V. V. Makarov, S. Kundu, D. V. Kirsanov, N. S. Frolov, V. A. Maksimenko, D. Ghosh, S. K. Dana, and A. E. Hramov, “Multiscale interaction promotes chimera states in complex networks,” *Communications in Nonlinear Science and Numerical Simulation*, vol. 71, pp. 118–129, 2019.
- [3] A. Andreev, N. Frolov, A. Pisarchik, and A. Hramov, “Chimera state in complex networks of bistable Hodgkin-Huxley neurons,” *Physical Review E*, vol. 100, no. 2, p. 022224, 2019.
- [4] D. Kulminskiy, V. Ponomarenko, M. Prokhorov, and A. Hramov, “Synchronization in ensembles of delay-coupled nonidentical neuronlike oscillators,” *Nonlinear Dynamics*, vol. 98, no. 1, pp. 735–748, 2019.
- [5] A. A. Badarin, S. A. Kurkin, A. A. Koronovskii, A. E. Hramov, and A. O. Rak, “Processes of virtual cathodes interaction in multibeam system,” *Physics of Plasmas*, vol. 25, no. 8, p. 083110, 2018.
- [6] A. Andreev and V. Maksimenko, “Synchronization in coupled neural network with inhibitory coupling,” *Cybernetics and Physics*, vol. 8, no. 4, pp. 199–204, 2019.
- [7] F. Parastesh, H. Azarnoush, S. Jafari, B. Hatef, M. Perc, and R. Repnik, “Synchronizability of two neurons with switching in the coupling,” *Applied Mathematics and Computation*, vol. 350, pp. 217–223, 2019.
- [8] E. Yilmaz, M. Ozer, V. Baysal, and M. Perc, “Autapse-induced multiple coherence resonance in single neurons and neuronal networks,” *Scientific Reports*, vol. 6, p. 30914, 2016.
- [9] A. Andreev, V. Makarov, A. Runnova, and A. Hramov, “Coherent resonance in neuron ensemble with electrical couplings,” *Cybernetics and Physics*, vol. 6, no. 3, pp. 135–138, 2017.
- [10] S. A. Kurkin, E. N. Pitsik, V. Y. Musatov, A. E. Runnova, and A. E. Hramov, “Artificial neural networks as a tool for recognition of movements by electroencephalograms,” in *ICINCO (1)*, 2018, pp. 176–181.
- [11] N. Frolov, V. Maksimenko, A. Lüttjohann, A. Koronovskii, and A. Hramov, “Feed-forward artificial neural network provides data-driven inference of functional connectivity,” *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 29, no. 9, p. 091101, 2019.
- [12] S. Kurkin, P. Chholak, V. Maksimenko, and A. Pisarchik, “Machine learning approaches for classification of imaginary movement type by meg data for neurorehabilitation,” in *2019 3rd School on Dynamics of Complex Networks and their Application in Intellectual Robotics (DCNAIR)*. IEEE, 2019, pp. 106–108.
- [13] A. N. Pisarchik, V. A. Maksimenko, A. V. Andreev, N. S. Frolov, V. V. Makarov, M. O. Zhuravlev, A. E. Runnova, and A. E. Hramov, “Coherent resonance in the distributed cortical network during sensory information processing,” *Scientific Reports*, vol. 9, no. 1, pp. 1–9, 2019.
- [14] V. Maksimenko, A. Badarin, V. Nedaivozov, D. Kirsanov, and A. Hramov, “Brain-computer interface on the basis of eeg system encephalan,” in *Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV*, vol. 10717. International Society for Optics and Photonics, 2018, p. 107171R.
- [15] E. Pitsik, N. Frolov, K. H. Kraemer, V. Grubov, V. Maksimenko, J. Kurths, and A. Hramov, “Motor execution reduces eeg signals complexity: Recurrence quantification analysis study,” *Chaos*, vol. 30, p. 023111, 2020.
- [16] N. Frolov and A. Hramov, “From theory to experimental evidence: Comment on “chimera states in neuronal networks: A review” by s. majhi, bk bera, d. ghosh and m. perc.” *Physics of life reviews*, vol. 28, pp. 125–127, 2019.
- [17] J. Keener and J. Sneyd, *Mathematical Physiology*. New York: Springer, 1998.
- [18] A. L. Hodgkin and A. F. Huxley, “A quantitative description of membrane current and its application to conduction and excitation in nerve,” *The Journal of physiology*, vol. 117, no. 4, pp. 500–544, 1952.
- [19] E. V. Pankratova and A. V. Polovinkin, “Resonant activation in a stochastic Hodgkin-Huxley model: interplay between noise and suprathreshold driving effects,” *European Physical Journal B*, vol. 45, p. 391, 2005.
- [20] J. A. White, J. T. Rubinstein, and A. R. Kay, “Channel noise in neurons,” *Trends in Neurosciences*, vol. 261, pp. 83–92, 2000.