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Control of dynamics of bistable neural network by an external pulse

Andrey V. Andreev^a, Nikita S. Frolov^a, Natalija A. Alexandrova^{ab}, Marija A. Chaban^{ab}

^aNeuroscience and Cognivite Technology Laboratory, Center for Technologies in Robotics and Mechatronics Components, Innopolis University, Universitetskaya Str. 1, Innopolis, 420500, Russia;

^bFaculty of Information Technologies, Saratov State University, Astrakhanskaja str., Saratov, 410600, Russia

ABSTRACT

We investigate the dynamics of individual Hodgkin-Huxley neuron in a multistable area where both stable fixed point and stable limit cycle coexist. We demonstrate a possibility of controlling neuron dynamics by a short pulse of the constant external current. Depending on the pulse time, duration and amplitude it can switch the neuron state from resting to oscillatory one and vice versa. We investigate the possibility of controlling the dynamics of a network of 100 bistable Hodgkin-Huxley neurons by a short external current pulse. We show that for certain values of the pulse parameters, such as amplitude, time length, and applying time, the pulse can force some neurons to change their dynamics.

Keywords: Complex network, Hodgkin-Huxley neuron, neural network, scale-free topology, external pulse

1. INTRODUCTION

Human brain is one of the most complex and interesting object for investigation. In recent years many researchers had done a lot of experimental studies of the brain.¹⁻⁷ But sometimes, it is not so easy to understand how the brain regions interact to each other on a neural level.^{8,9} In that cases it is useful to do numerical simulation.¹⁰

Numerical simulation of the networks of different nature and investigation of its dynamics has attracted much attention in recent years.¹¹⁻¹⁶ Especially, the networks of biological neurons is of interest due to it allows investigating the brain properties at the microscopic level and getting a better understanding of some phenomena.¹⁷⁻²¹ Usually, dynamics in a neuronal network is considered by supposing that every neuron in the network is monostable. But the bistability regime in oscillatory systems is known to be of special interest due to a variety of hidden unexpected phenomena.^{22,23} And also it is of interest in terms of control.

Controlling the internal state of complex systems is of fundamental interest²⁴⁻²⁶ and enables applications in biological, technological, and social contexts. Especially, much attention is paid to controlling the neural networks.^{25,27,28} That can make a contribution to the development of signal classifiers based on interconnected biological neurons.^{29,30}

The most popular biological neuron models used in the mathematical simulation are Hodgkin-Huxley (HH),³¹ FitzHugh-Nagumo (FN),³² and Hindmarsh-Rose (HR)³³ ones. In our research, we use HH neuron due to its most realistic behavior and biological inspiration.

In the paper, we investigate the dynamics of individual HH neuron in a multistable area where both stable fixed point and stable limit cycle coexist. We also demonstrate a possibility of controlling a neuron dynamics by a short pulse of the constant external current changing the neuron's regime from resting to oscillatory one and vice versa. Then we investigate how the short external pulse influences the dynamics of the networks of 100 identical bistable Hodgkin-Huxley neurons with scale-free topology. We show that for certain values of the pulse parameters, such as amplitude, time length, and applying time, the pulse can force some neurons to change their dynamics.

Further author information: (Send correspondence to A.V. Andreev)
A.V. Andreev: E-mail: andreevandre1993@gmail.com

2. NUMERICAL MODEL

We consider one Hodgkin-Huxley neuron and the network of $N = 100$ Hodgkin-Huxley neurons. The time evolution of the transmembrane potential of the HH neurons is given by³¹

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

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, $i = 1, \dots, N$, $g_{Na}^{max} = 120 mS/cm^2$, $g_K^{max} = 36 mS/cm^2$ and $g_L^{max} = 0.3 mS/cm^2$ respectively denote the maximal sodium, potassium and leakage conductance when all ion channels are open. $V_{Na} = 50 mV$, $V_K = -77 mV$ and $V_L = -54.4 mV$ 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 $m^3 h$ 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 by³⁴

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

$$\beta_m(V) = 4 \exp(-V/18) \quad (4)$$

$$\alpha_h(V) = 0.07 \exp(-V/20) \quad (5)$$

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

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

$$\beta_n(V) = 0.125 \exp(-V/80) \quad (8)$$

I_i^{syn} is the total synaptic current received by neuron i . We consider coupling via chemical synapses. The synaptic current takes the form³⁵

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

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 $\alpha(t) = e^{-t/\tau_{syn}} \Theta(t)$, 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.

3. RESULTS

External current I^e controls the dynamics of the neuron: depending on it the neuron can be either in “silent” or spike generation regime. So the current amplitude is a system bifurcation parameter. It was shown in³⁶ and we demonstrate it in Fig.1(a) that there is a small multistable area of I^e where both regimes coexist. For $I^e < 6.24$ only the stable steady state exists, and for $I^e > 9.78$ there is only a limit cycle. So the point $I^e = 6.24$ is a threshold point for a neuron due to it starts generating spikes and transmitting information. According to³⁶ further increasing the external current leads to decreasing oscillation amplitude and transition to steady state through Hopf bifurcation. But we are not interested in the investigation of that area.

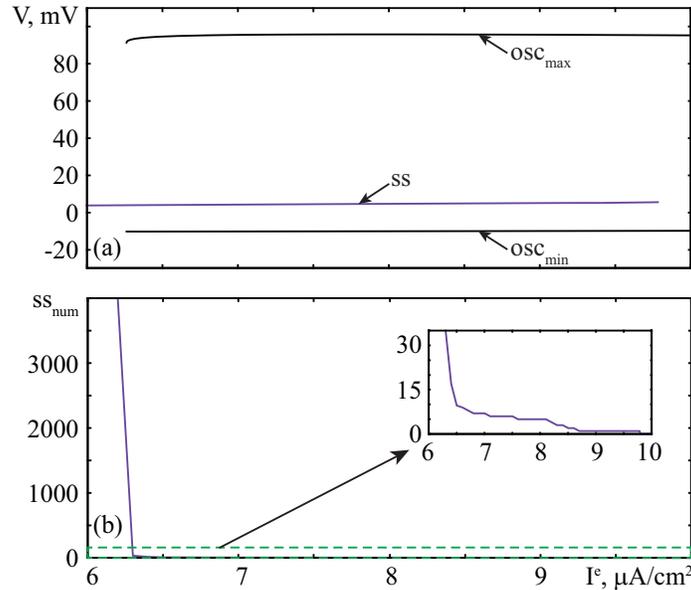


Figure 1. (a) Bifurcation diagram of one HH neuron, with the external current I^e as the bifurcation parameter. Here, ss denotes a stable steady state, osc_{max} and osc_{min} denote the maximum and minimum of a limit cycle. (b) Basin stability measure of ss attractor.

In order to investigate the basin stability³⁷ (BS) of steady state and limit cycle: $BS = L/M$, where $M = 4000$ is the number of different random initial conditions for each value of external current, L is the number of them iterated into the first or the second one. Fig.1(b) demonstrates this dependence. One can see that the relative size of steady state basin sharply reduces when the limit cycle appears, and for $I^e = 6.3\mu A/cm^2$ it is only 0.875% of its initial size and continues to decrease for higher external current.

We investigate the possibility of controlling neural dynamics using the short external pulses (Fig.2). We choose external current as follows:

$$I^e = \begin{cases} 6.5 & t < t_1 \\ 10.5 & t_1 \leq t \leq t_1 + 5 \\ 6.5 & t_1 + 5 < t < t_2 \\ 10.5 & t_2 \leq t \leq t_2 + 5 \\ 6.5 & t > t_2 + 5 \end{cases} \quad (10)$$

where t_1 and t_2 are the applying times of the first and the second pulses respectively. We choose $I^e = 6.5\mu A/cm^2$ as the constant external current because the size of steady state basin is relatively not so small for this value. So we choose the initial conditions corresponding to the steady state, and apply the 5 ms pulse of the extended external current of amplitude $I^e = 10.5\mu A/cm^2$ that on $4\mu A/cm^2$ higher than the constant one at $t_1 = 205$ ms. These values of amplitude and time length are enough to change the neuron dynamics from “silent” to oscillatory. It happens because according to Fig.1(a) for this current amplitude there is only oscillatory regime exists in the system. During the pulse, membrane potential has time to leave from the steady state basin existing in the constant current case, and after the pulse, neuron stays in the periodic cycle and continues to generate spikes (red curves in Fig.2). Then after some time, we apply the second pulse identical to the first one. Depending on the applying time t_2 neuron dynamics can either be changed to “silent” or it continues to oscillate. As one can see from Fig.1, the pulse parameters (length, amplitude and applying time) should be optimal to make the neuron’s phase trajectory be in the steady state basin after applying the pulse. For the values of the pulse length and amplitude, we choose the pulse should be applied during the time period when its membrane potential V slowly increases after spike generation. During the pulse (blue curve) phase plane trajectory goes on a new periodic orbit corresponding higher external current. That orbit crosses the area of steady state basin for $I^e = 6.5\mu A/cm^2$, and if after the pulse the trajectory will be inside that area, it iterates into the steady state.

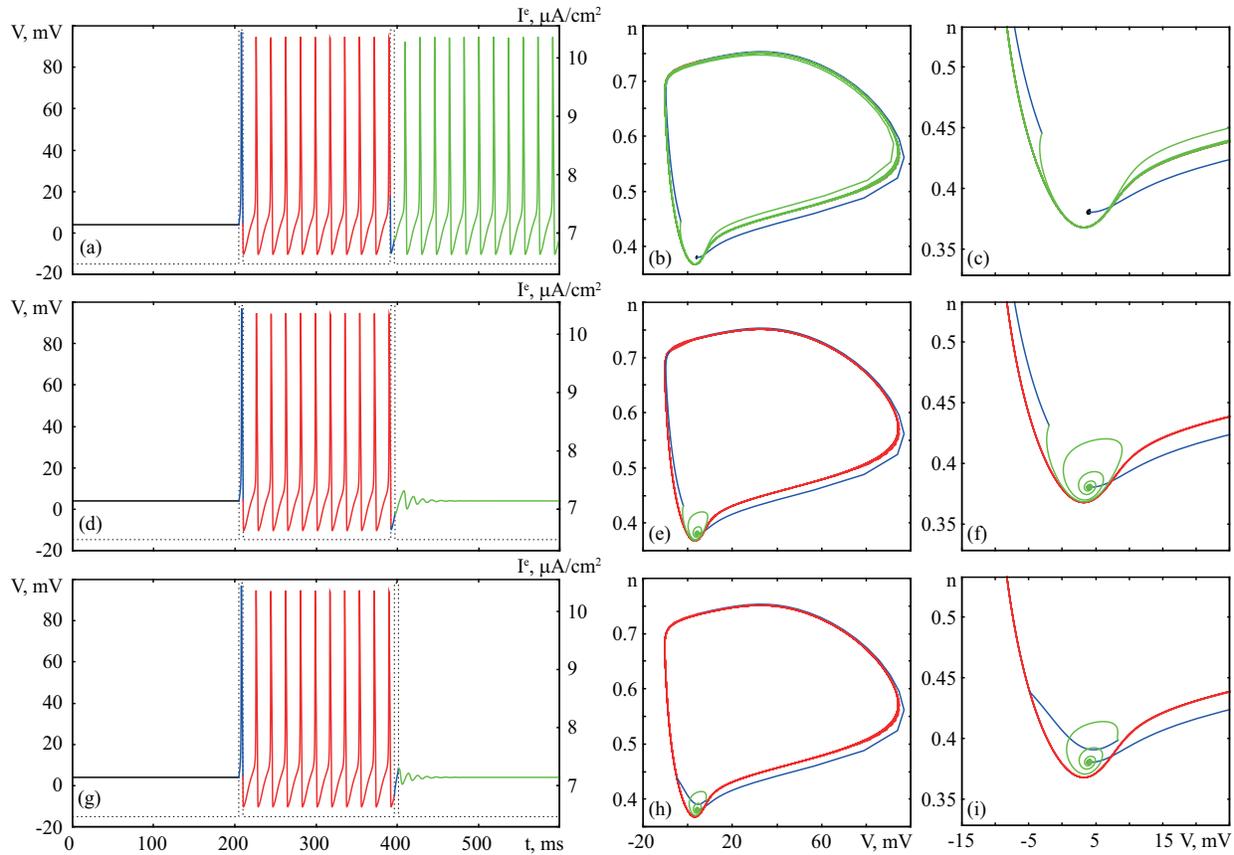


Figure 2. (a,d,g) The time series of membrane potential oscillations of one Hodgkin-Huxley neuron, (b,e,h) the phase planes of the corresponding signals and (c,f,i) the increased parts of them. In all 3 cases we apply a short pulse of increased external current with amplitude of $10.5 \mu A/cm^2$ and length of $5 ms$ twice: the first pulse is applied at $t_1 = 205 ms$, the second one at $t_2 = 391.5 ms$ (a-c), $t_2 = 392 ms$ (d-j), $t_2 = 396.5 ms$ (g-i). The colors correspond to the parts of the signals: “black” – before the first pulse, “blue” – a pulse period, “red” – between pulses, “green” – after the second pulse. $I^e = 6.5 \mu A/cm^2$ at the times out of pulse.

The top panels in Fig.2(a-c) represent the case when we apply the pulse too early and after the pulse phase plane trajectory stays in limit cycle basin, so it returns to the periodic orbit corresponding for $I^e = 6.5 \mu A/cm^2$ (green line). But if we apply the pulse $0.5 ms$ later, neuron trajectory goes to steady state eventually (d-f). The middle and the bottom panels in Fig.2 correspond the earliest and the latest applying time leading to the steady state within the limit cycle period respectively.

As one can see the steady state point is inside the limit cycle and increasing the external current amplitude leads to changing the last one’s trajectory making it crossing the steady state basin existing for lower current.

Now we investigate the possibility of controlling the dynamics of the network of 100 HH neurons with scale-free topology. Scale-free topology is a well-known and widely-used connectivity paradigm in computational studies of local microcircuits since such connectivity has been observed in many functional brain regions via neuroimaging and electrophysiological studies.^{38,39} Scale-free topology was generated by Barabási–Albert algorithm.⁴⁰

As we discussed before, the pulse is able to change neural dynamics from resting to spiking one and vice versa. So in that case, if we choose the parameters corresponding to the case when all elements in the system are active and bistable, we could expect that a part of them will change its dynamics after the pulse.

We choose pulse length is equal to $5 ms$, but during the pulse, the external current amplitude is only $0.5 \mu A/cm^2$ higher than outside the pulse. We choose $I^e = 7 \mu A/cm^2$ outside the pulse and $g_c = 0.0025$

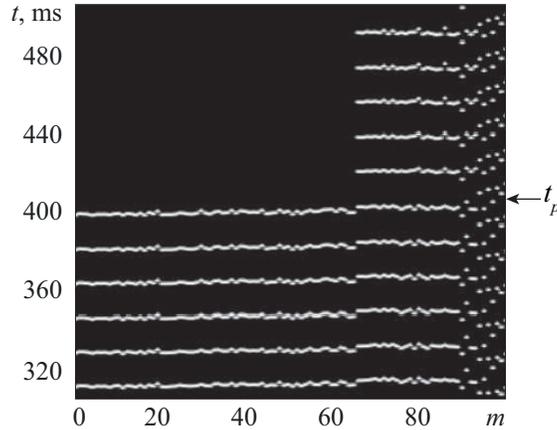


Figure 3. Time series of all neurons calculated for scale-free topology. We apply the external pulse of 5 ms duration at $t_p = 405$ ms. I^e is described by Eq. (11), $g_c = 0.0025$.

corresponding to the case when all neurons are active, but in the phase plane, there are 2 coexisting stable states. So the external current is defined as follows:

$$I^e = \begin{cases} 7.0 & t < t_p \\ 7.5 & t_p \leq t \leq t_p + 5 \\ 7.0 & t > t_p + 5 \end{cases} \quad (11)$$

where t_p is the time of the pulse applying.

Fig. 3 illustrates the dynamics of all neurons before ($t < 405$ ms) and after ($t > 410$ ms) the pulse for scale-free topology. All elements are sorted by averaged inter-spike interval calculated after the pulse. As one can see initially all neurons generate spikes but when we apply the pulse a part of them ($n \geq 66$) remains in that state while another one ($n \leq 65$) iterates to the steady state. The reason why some neurons do not change their dynamics while others do is the state in which the neuron is, when the pulse is applying. So changing t_p can lead to the case when another group of neurons will fire. As we discovered before, the neuron has an optimal time range regarding the spike generation time applying pulse in which its dynamics will change. And each one has its own time range. So as there is no full synchrony in the neural dynamics only a part of elements is affected by the pulse. But if the pulse time satisfies to the time ranges of each neuron all of them change their dynamics to the resting one. And also it can be a reverse situation when the pulse time does not satisfy any neuron in the network and all of them stay active.

4. CONCLUSION

In this paper, we have investigated the dynamics of individual HH neuron in a multistable area where both stable fixed point and stable limit cycle coexist. A possibility of controlling a neuron dynamics by a short pulse of the constant external current changing its regime from resting to oscillatory one and vice versa has been demonstrated. It is possible because the steady state point is inside the limit cycle and increasing the external current amplitude leads to changing the last one's trajectory making it crossing the steady state basin existing for lower current.

We have investigated how the short external pulse influences on the dynamics of the networks of 100 identical bistable Hodgkin-Huxley neurons with scale-free topology. We have shown that for certain values of the pulse parameters, such as amplitude, time length, and applying time, the pulse can force some neurons to change their dynamics.

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