Local and Global Activities of Izhikevich Neuron Model in Networks

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Abstract— **It is important to investigate the phenomena in networks composed of neuron models. In our previous work, we have proposed a method to explain the phenomena in the whole network by nonlinear time-series analysis. In this study, we will clarify the relationship between the phenomena at the constituent nodes of the network and the overall phenomena.**

Keywords; neuron data, nonlinear time-series analysis

I. INTRODUCTION

Uncovering the evolutionary process of the brain is one of the most important steps in understanding the brain systems that perform higher-order information processing. In order to make clear the mechanism of the brain, burst detection and burst pattern analyzes methods are developed, which are used in various fields [1]. Nonlinear time series analysis is a different approach from linear time series analysis because it can capture the characteristics of a time series in a nonlinear manner [2]. We consider that this nonlinear time series analysis is effective for analyzing the activity patterns of the brain.

Our research group has proposed a method to extract features other than burst information from brain activity patterns by visualizing features of the entire network using attractor embedding . In this study, spike firing rates were calculated from raster plots obtained from 1024 electrodes, and attractor embedding, a nonlinear analysis method, was applied to the time series. We applied nonlinear time-series analysis to three sets of time-series data from a neuronal culture measured at days in vitro (DIV) 15, 20 and 30, respectively [3]. By using computer simulations, we confirmed that the characteristics of these neuronal networks change across different DIV and that the proposed visualization methods are suitable to capture the essence of these changes [4].

However, the relationship between the results obtained from the spike firing rate of an entire neuron region and what it represents for the neuron information here is unclear. Additionally, we consider that it is required to construct a model using mathematical neuron model producing burst patterns, because it is difficult to obtain real biological neuron data.

In this study, we consider the relationship between local and global activities of the networks which is composed of Izhikevich neuron model. By using attractor reconstruction, we confirmed that differences in local and global activity status.

II. IZHIKEVICH NEURON MODEL

Izhikevich neuron model efficiently produces a wide variety of neuron spiking and bursting dynamics. The Izhikevich neuron model is described by the following equations.

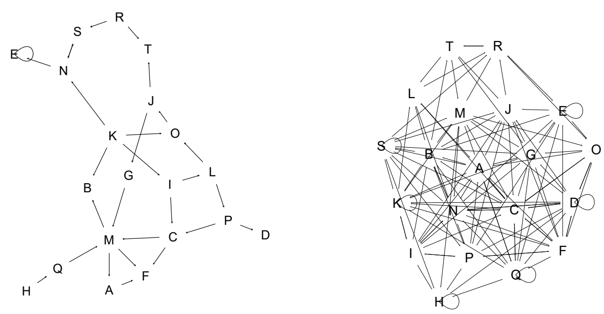
$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I_{ex}$$

$$\frac{du}{dt} = a(bv - u)$$

$$\text{if } v > 30 \text{ mV, then } v \leftarrow c \text{ and } u \leftarrow u + d.$$

Where v represents the membrane potential of the neuron, u represents a slow membrane recovery variable, accounting for the activation of K^+ ion currents and inactivation of Na^+ ion currents. I_{ex} denotes the excitatory input current. In the computer simulations, 20 neurons were coupled randomly with the coupling probability p. The ratio of excitability and inhibitory neuron is 0.8 and 0.2, respectively.

Figure 1 shows the two types of network models for this study. It is confirmed that the Network B has more connections than the Network A.



(a) Network A (p=0.1). (b) Network B (p=0.3).

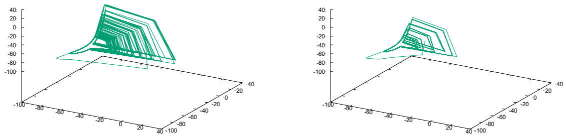
Fig. 1 Network models (N=20) depending on the coupling probability p.

III. SIMULATION RESULTS

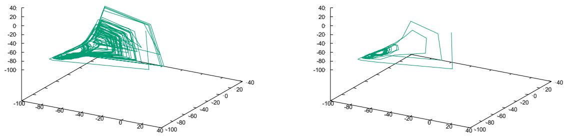
A. *Local Activity in the Networks*

At the first step, we investigate local neuron activity in the network. Figures 2 and 3 show the simulation results of attractor reconstruction of the spiking activity of a typical node in Network A and B.

In the case of Fig. 2, nodes Q and S behave active and the other nodes show periodicity. While in the case of Fig. 3, all nodes behave very active.

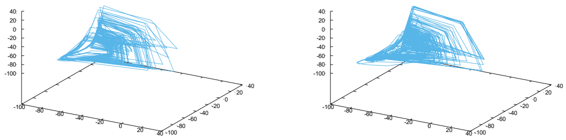


(a) node Q. (b) node R.

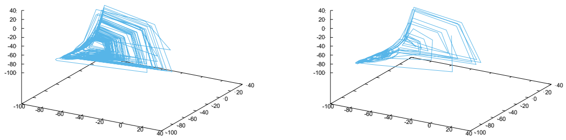


(c) node S. (d) node T.

Fig. 2 Attractor reconstruction of Network A.



(a) node Q. (b) node R.



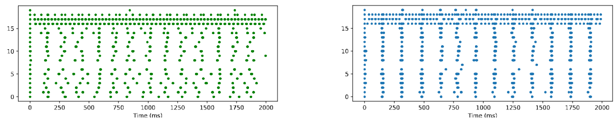
(c) node S. (d) node T.

Fig. 3 Attractor reconstruction of Network B.

B. *Global Activity in the Network*

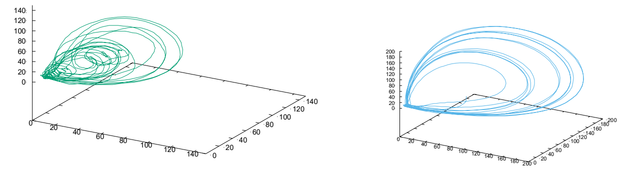
Next, global activity in the network is investigated. Figure 4 shows the raster plot obtained from the Networks A and B. After that, we calculate the spike rate at time bins, then time-series data of the whole network is obtained.

Figure 5 shows the simulation results when neuronal timeseries data is embedded in 3-dimensional space with time delay $\tau = 10$. From this figure, we confirm that two networks exhibit a clear structure, because the orbit draws in certain range and does not move about randomly. Furthermore, in the case of the Network B, the size of the attractor is larger and the behavior of the orbit is periodicity.



(a) Network A. (b) Network B.

Fig. 4 Raster plot.



(a) Network A. (b) Network B.

Fig. 5 Attractor reconstruction of whole network.

IV. CONCLUSIONS

In this study, we investigated the local and global activities of Izhikevich neuron model using attractor reconstruction. In a network with few connections, there are active and inactive nodes, whereas a network with many connections is composed of active nodes overall. The investigation of overall neuronal activity shows more complex behavior in networks with fewer connections, and more periodicity in networks with more connections.

For the future works, we would like to perform a quantitative evaluation of the obtained attractor reconstruction. In addition, since we have investigated one specific network model, more statistical analysis is needed.

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