Feature Extraction of Neuron Group Composed of Two Different Firing Patterns Using Nonlinear Analysis

Yoko Uwate and Yoshifumi Nishio
Dept. of E. E. Eng., Tokushima University
2-1 Minami-Josanjima Tokushima 770-8506 Japan
Email: {uwate, nishio}@ee.tokushima-u.ac.jp

Abstract— **In our previous work, feature visualization using non-linear analysis has been proposed for time series of spike firing rates of neuronal activity. In this study, we investigate the neuronal activity of two mixed types of neurons: regular spiking and chattering. We investigate the effects of an increased rate of the number of chattering neurons.**

Keywords; neuronal activity, nonlinear time-series analysis

I. INTRODUCTION

Understanding how brain circuits develop and operate is a major goal for many neuroscience projects. Burst patterns in neuronal networks may have an important role in information processing in the brain. Therefore, detecting and analyzing burst patterns are investigated in various fields. Although it is important to study burst patterns in order to understand the correlation and communication processes of neurons, unveiling a structure of the whole neuronal network is also required.

On the other hands, nonlinear time-series analysis is a useful tool for characterizing the dynamics behind the observed time-series data. The neuronal data obtained from living neurons should be high-dimensional and dynamic nature. In such case, nonlinear time-series analysis can be used to characterize the neuronal data.

Previously, we proposed the method of feature extraction of neuronal activity using nonlinear time series analysis [1]. We also investigated attractor reconstructions obtained from time series data of spike rate [2]. By using the simulations, we confirmed that the attractor of the network with high connectivity is larger size than the network with low connectivity. However, the complexity of attractor of network with low connectivity is higher than the network with high connectivity. In such simulations, only one firing pattern is used. In the real brain networks, there are several types of firing patterns.

In this study, we investigate feature of neuron group composed of two different firing patterns using nonlinear analysis. We confirm that the neuronal activity with high ratio of chattering has high spike rate in the whole network.

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.

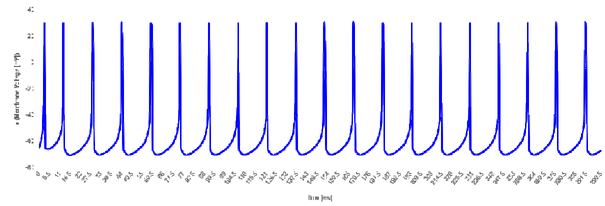
$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I_{ex}$$

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

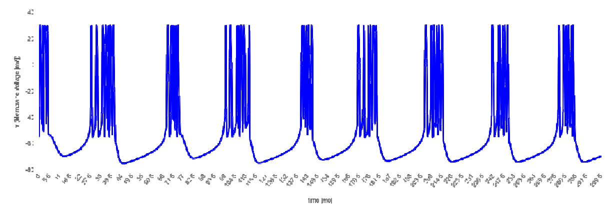
$$\text{if } v > 30 \text{ mV, then } v \leftarrow c \text{ and } u \leftarrow u + d.$$

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, 100 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 different firing patterns. Fig. 1 (a) shows regular spiking and Fig. 1 (b) shows chattering. We investigate the effects of an increased rate of the number of chattering neurons.



(a) Regular spiking.



(b) Chattering.

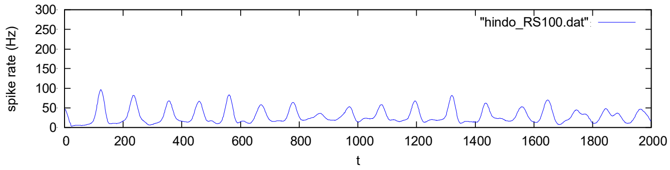
Fig. 1. Two different firing patterns.

III. Simulation Results

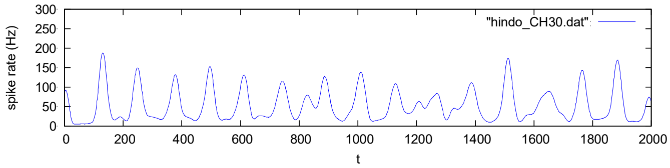
The simulation results are shown in below subsections.

A. Spike Rate

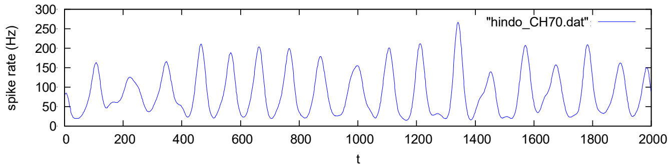
Figure 2 shows the spike rate which is calculated the spike times during a certain bin by changing the ratio of chattering neurons. By increasing the ratio of chattering neurons, the peak of spike rate becomes large.



(a) Chattering neurons: 10%.



(b) Chattering neurons: 30%.



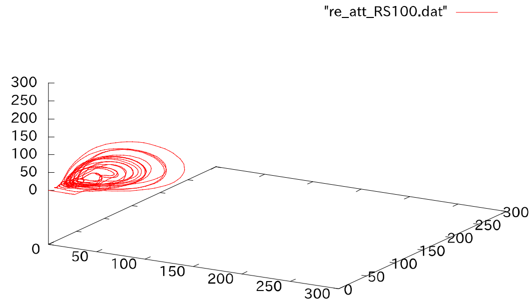
(c) Chattering neurons: 70%.

Fig. 2. Spike rate time series.

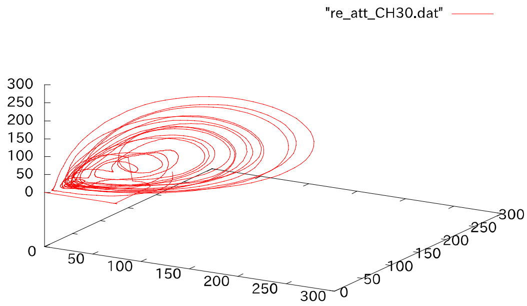
B. Attractor reconstruction

The attractor of dynamical systems can be reconstructed topologically in the embedding space from Takens' theorem [3].

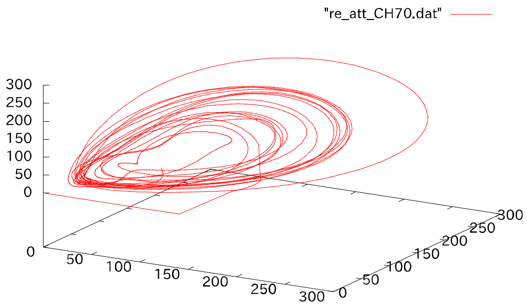
Figure 3 shows the simulation results when neuronal time-series data is embedded in 3-dimensional space with time delay 10. From these figures, we confirm that the size of attractor of chattering neuron 70% is largest than the others. However, no information other than the size of the attractor can be understood from these results. We need to investigate the complexity of the attractors by using Poincare section.



(a) Chattering neurons: 10%.



(b) Chattering neurons: 30%.



(c) Chattering neurons: 70%.

Fig. 3. Attractor reconstruction.

IV. Conclusions

We investigated feature of neuron group composed of two different firing patterns using attractor reconstruction as nonlinear analysis. We confirm that the neuronal activity with high ratio of chattering has large size of attractor.

In the future works, we would like to analyze the spike rate time series using other nonlinear techniques in order to understand the characteristics of neuronal activity in more detailed.

References

[1] Y. Uwate, M. E. J. Obien, U. Frey and Y. Nishio, “Time Series Analysis of Neurons and Visualization of Network Characteristics”, Proc. of NCSP’19, 2019.

[2] Y. Uwate, M. E. J. Obien, U. Frey and Y. Nishio, “Modeling of Bursting Neurons and Its Characteristic using Nonlinear Time Series Analysis”, Proc. of NCSP’20, March, 2020.

[3] F. Takens, “Detecting Strange Attractors in Turbulence,” In D.A. Rand and B.-S. Young, editors, Dynamical Systems and Turbulence, vol. 898 of Lecture Notes in Mathematics, pp. 366–381, Warwick 1980, 1981.