Nonlinear Time Series Analysis of Spike Data of Izhikevich Neuron Model

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

Marie Engelene J. Obien and Urs Frey
MaxWell Biosystems
Albisriederstrasse 253, Zurich,
8047 Switzerland
Email: {marie.obien, urs.frey}@mxwbio.com

Abstract— **It is well known that burst patterns of neuronal networks may play an important role in information processing in the brain. We consider that it is advantageous to construct a model using mathematical neuronal models producing burst patterns, because it is such models are easier to study and more accessible as compared to real biological neuronal data. In this study, we use the Izhikevich neuron model to produce burst patterns and apply a recurrence plot density entropy to the Izhikevich neuron data.**

Keywords; neuron data, nonlinear time-series analysis

I. Introduction

Burst patterns within neurons may play an important role in information processing in the brain. Therefore, burst detection and burst pattern analyzes methods are developed, which are used in various fields [1]. Although it is important to study burst patterns, as these can relate to network syn- chronicity and synaptic connectivity, unveiling the structure of the whole neuronal network is also required. Nonlinear time-series analysis is a useful tool for characterizing the dynamics behind observed time-series data [2]. Typically, neuronal data obtained from living neurons is high-dimensional and dynamic data, therefore nonlinear time-series analysis is suitable to characterize neuronal data. Previously, we pro- posed a visualization method for bursting patterns of whole neural networks using nonlinear time series analysis [3]. 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. 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.

However, it is difficult to extract the ground-truth of the underlying network morphology for data obtained from real biological neuronal networks. To relate these time-series analysis results to the underlying network morphology, it is re- quired to construct a model using mathematical neuron models producing such burst patterns. In our previous study, we propose a visualization method of network characteristics of burst patterns obtained from Izhikevich neuron model using nonlinear time-series analysis. From the simulation results, we confirm that the Izhikevich neuron model shows similar development stages as biological neurons, by controlling the parameters of the coupling probability and strength [4].

In this study, we apply recurrence plot density entropy to spike burst data generated from Izikevich neuron model and investigate the characteristics of spike burst data.

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, 1,000 neurons were coupled randomly. The ratio of excitability and inhibitory neuron is 0.8 and 0.2, respectively. The parameters of the Izhikevich neuron model are fixed with a=0.02, b=0.2, c=-50 and d=8. By using these parameters, the Izhikevich neuron model produces tonic spiking as shown in Fig. 1.

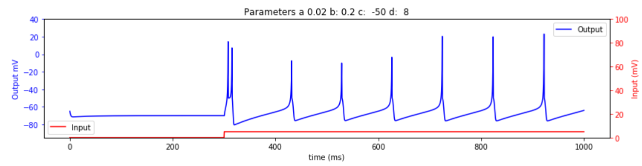
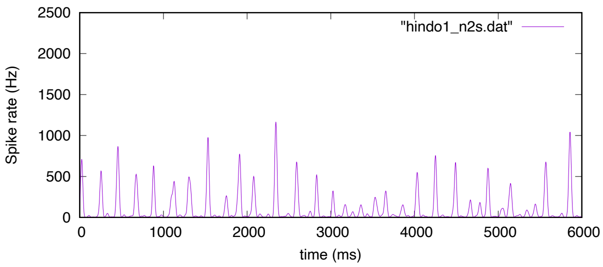
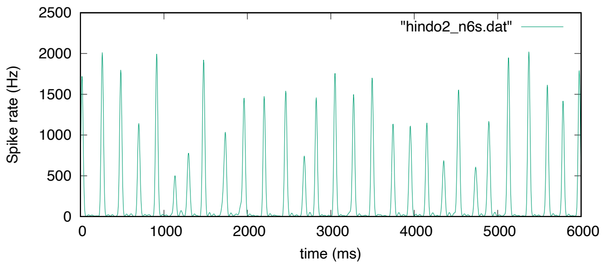


Fig. 1. Tonic spiking of the neuron network model.

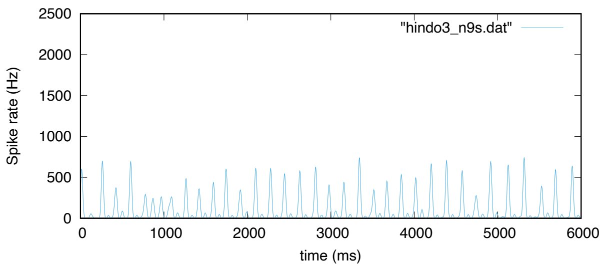
The coupling probability (p) of the network and the coupling strength (g) of excitability neurons are important parameters for modeling the development of neurons. Figure 2 shows the network activity of 1,000 neurons, the firing rate during a fixed bin, for different values of the coupling probability and strength.



(a) p=0.2, g=1.6 [mV]



(b) p=0.08, g=2.2 [mV]



(c) p=0.03, g=2.5[mV]

Fig. 3 Time series data of the simulated neuronal network.

III. Nonlinear Time Series Analysis

A. Recurrence Plot Density Entropy (RPDE)

Recurrence time is calculated as the distance between the points on the vertical line of the recurrence plot (RP) [5], [6]. Little *et al.* have proposed the Recurrence Period Density Entropy method (RPDE). In this method, the iterations of each point to the neighborhood ε are tracked, and the resulting time intervals are used to build a histogram of iteration times. This histogram is used to calculate the recurrence period density function. The normalized entropy of this density is defined as following equation [7].

$$H_{norm} = -(lnT_{max})^{-1} \sum_{t=1}^{T_{max}} P(t) lnP(t)$$

The value of H_{norm} changes in the range from zero to one. For the periodic signals, H_{norm}=0, while the uniform white noise, H_{norm}=1.

B. Simulation Results

Figure 4 shows the simulation results of the RPDE of 10 average. The spike rate of Fig. 3 (b) has highest RPDE. From this result, it was found that the characteristics of the neuron spike influence the coupling strength and coupling probability connection rate of the network. When the coupling strength or the coupling probability are small, the periodicity of the neuron activities becomes high (Fig. 4 (a) and (c)).

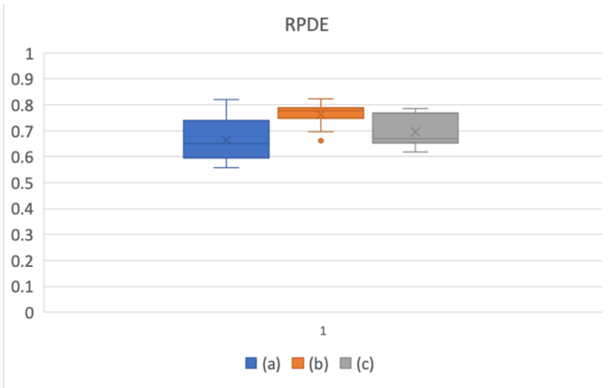


Fig. 4 Results of RPDE (H_{norm}).

IV. Conclusions

In this study, we investigated the characteristics of neuron spike data of Izhikevich neuron model using recurrence plot density entropy. By using the computer simulations, we confirmed that the spike data have more periodicity when the network parameters are set with strong coupling probability and weak coupling strength or weak coupling probability and strong coupling strength.

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