Visualization of Neuron Data using Nonlinear Technic

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Abstract— **In our previous study, we have proposed the method to use nonlinear time-series analysis to apply to neuronal data for visualizing a characteristic of neurons. We set up three types of neuron data which are observed at different days. By applying three nonlinear time-series analysis, we confirmed that the youngest neuron has strong activity and the neuronal behavior settles down as the day goes on. In this study, we investigate the effect of the delay parameter of attractor reconstruction of nonlinear time-series analysis. From observed results, we can see that the appropriate value of delay parameter exists to display the network characteristics.**

Keywords; neuron data, nonlinear time-series analysis

I. INTRODUCTION

Understanding how brain circuits develop and operate is a major goal for recent neuroscience project. Burst patterns within neurons may have some important role for operating information processing in a brain. Therefore, to develop detecting and analyze burst pattern are investigated in various fields [1]. Although it is important to study burst pattern in order to make clear correlation and communication process between neurons, unveiling a structure of the whole neuronal network is also required. While, nonlinear time-series analysis is a useful tool for characterizing about the dynamics behind observed time-series data [2]. The neuronal data obtained from living neurons should be high-dimensional and dynamic data. Then nonlinear time-series analysis matches well to characterize the neuronal data.

Then, three techniques: attractor reconstruction, recurrence plot and Lyapunov exponent are applied. In our previous study, we focus on time-series data generated from spike time data of neurons. The spike times are detected at each electrode with high-density microelectrode array (HD-MEA) system called MaxOne [3]. There are 1024 electrodes in total and the sampling rate is 20kHz. The recording time is 60 seconds. First, in order to figure out the characteristics of spike time, we display the spike time as raster plot. Next, we change the spike time data to time-series data depending on the spike rate at certain range. Finally, we apply nonlinear time-series analysis to three time-series data of neurons, which are measured by day 15, 20 and 30, respectively. By using computer simulations, we confirm that the characteristics of neuron are different between youngest and oldest neurons [4].

In this study, we focus on the delay parameter of attractor reconstruction which is defined by Takens' theorem. The delay parameter is important role for displaying the network characteristics. By changing the delay parameters, we obtained the different shapes of attractors in 3-dimensioanl space. From observed results, we can see that the appropriate value of delay parameter exists to display the network characteristics.

II. NEURON DATA SET

A. Measurement Platform

We used a CMOS-based high-density microelectrode array (HD-MEA) system called MaxOne (MaxWell Biosystems, Basel, Switzerland) composed of 26,400 platinum electrodes in a regular grid format with 17.5 µm electrode center-to-center distance (3,265 electrodes/mm2). Up to 1,024 electrodes could be simultaneously recorded by routing the electrodes to low-noise read-out channels through a flexible switch-matrix approach [5]. On-chip circuitry was used to amplify (0-78 dB programmable gain), filter, and digitalize (10-bit, 20 kHz) the recorded signals. Online spike detection was performed by the MaxLab Live software (threshold: x5 RMS noise).

B. Cortical Cell Cultures

Primary cell cultures were prepared as described in Ref. [6] in accordance to Swiss Federal Laws on animal welfare. Briefly, cells from embryonic day 18 Wistar rat cortices were dissociated in 2 ml of trypsin with 0.25~% EDTA (Invitrogen, California, USA) with trituration. The cultures were maintained inside an incubator to control environmental conditions in 1 ml of growth medium (partially replaced twice per week).

C. HD-MEA Extracellular Recordings

The MaxOne HD-MEA recording setup was placed in a recording incubator (65~% humidity) for a control of environmental conditions (5~% CO2). During experiments, the MaxOne chips were transferred to the recording incubator and covered with sterilized lids to minimize media evaporation. Figure 1 shows the raster plot obtained from Day 15, using 1024 electrodes. Next, we calculate the spike rate at a certain range, then time-series data is obtained as shown in Fig. 2.

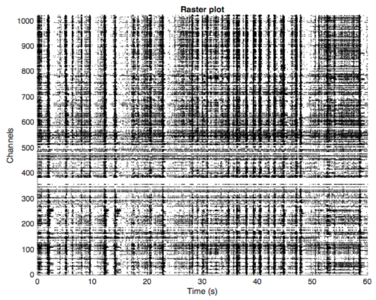


Fig. 1. Raster plot of neurons from 1024 electrode (Day 15).

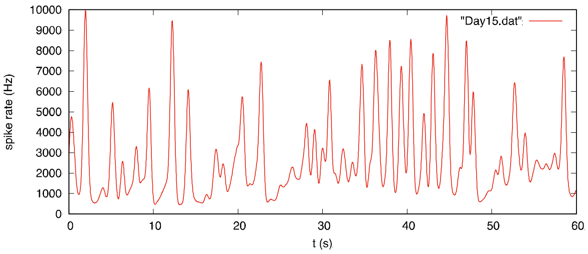


Fig. 2. Time series data from all neurons (Day 15).

III. Simulation Results

The attractor of dynamical systems can be reconstructed topologically in the embedding space from Takens' theorem [7]. The state vectors in the reconstructed m-dimensional embedding space are defined by

$$y(t) = \{x(t), x(t+\tau), , x(t+(m-1)\tau)\}$$

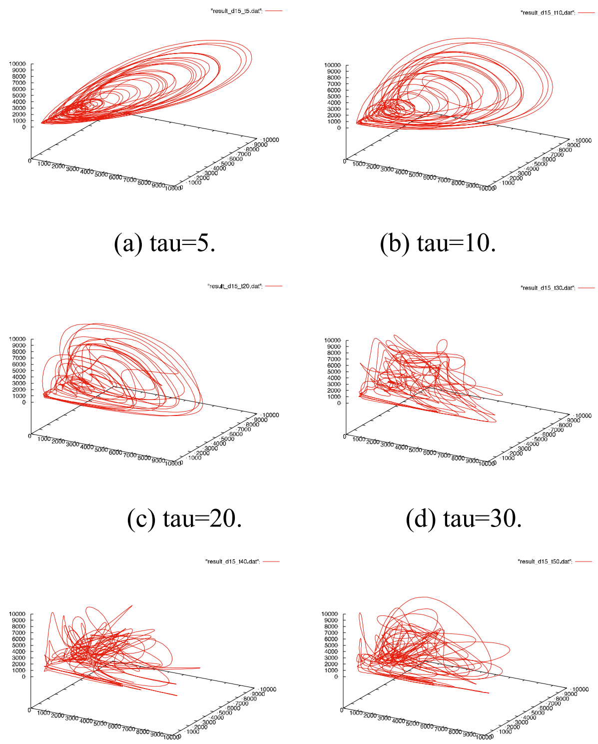
where x(t) means a scalar time series and tau is the delay time.

Figure 3 shows the simulation results when neuronal time-series data is embedded in 3-dimensional space by changing the delay time tau. From these figures, we confirm that the neuron have a structure when the tau is fixed with smaller than 20, because the orbit draws in certain range, does not move about randomly. While, when the tau is set to larger than 30, the behavior of the orbit is complex. To evaluate the network characteristics, it is better to fix the delay parameter tau<20 to obtain the structure.

IV. Conclusions

In this study, we changed the delay parameter of attractor reconstruction. The delay parameter is important role for displaying the network characteristics. By changing the delay parameters, we obtained the different shapes of attractors in 3-dimensioanl space. From observed results, we can see that the appropriate value of delay parameter exists to display the network characteristics.

In the future works, we would like to calculate the characteristics of attractor reconstruction results, and to use more different types of neuronal data. Applying classification of neuronal data is also our future works.



(a) tau=5. (b) tau=10.

(c) tau=20. (d) tau=30.

(e) tau=40. (f) tau=50.

Fig. 3. Attractor reconstruction.

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