2025 International Symposium on Nonlinear Theory and Its Applications,
NOLTA2025, Naha city, Okinawa, Japan, October 27-31, 2025

Investigating Growth-Dependent Evolution in Neuronal Chaos Through 1D-CNN Classification

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Abstract—In this study, we investigate how the chaotic characteristics of neuronal signals obtained from the actual Wister rat brain change during the growth process. To achieve this, we first constructed a 1-dimensional convolutional neural network (1D-CNN) to classify time series generated from a system of coupled Izhikevich neurons. From the results of inputting time series obtained from real neuronal signals into the trained 1D-CNN, we confirmed that the distribution of chaotic neurons changes with growth.

1. Introduction

Research on the brain and chaos theory plays an important role in understanding the complex activities and nonlinearity of the brain. It is believed that neural activity exhibits chaotic behavior, which enables information processing and adaptive responses, and chaos theory has been applied to predict cognitive function, consciousness and even neurological disorders [1], [2].

In recent years, developments in high-density microelectrode array (HD-MEA) have made it possible to measure many neuronal signals at once [3]. Neuronal signals recorded by HD-MEA are often analysed linearly, e.g. by Fourier transforming time series of firing frequencies, to understand the rhythm of neural activity [4]. However, as neuronal signals have very complex behavior, it was considered that new features could be detected by nonlinear analysis rather than linear analysis.

We have previously performed attractor embedding and recurrent plot visualization on time series of neuronal signals from real rat brains as a nonlinear analysis [5]. Although these methods can capture neuronal activity in a nonlinear concept, they are limited to visualization and quantitative evaluation and detailed explanation are difficult. The Lyapunov index and fractal dimension were also calculated to assess the complexity of the neuronal signal time series. However, the Lyapunov exponent could only determine whether the signal was chaotic or not, while the fractal dimension could not be calculated because the slope of the correlation function did not converge [6].

In this study, a deep learning model is proposed to classify the chaotic features of the time series of neuronal signals. 1D-CNN is used as the neural network model. The Izhikevich neuron model's time series of signal patterns are also used as training and validation data. The Izhikevich neuron model is a good model of real neurons as it can generate a variety of spike sequences [7], [8]. The chaos features are expressed in terms of the number of neurons generating chaos.

As a simulation, the first step is to classify five different time series with different numbers of neurons generating chaos of the Izhikevich neuron model. Finally, we investigated the classification results when time series of neuronal signals from actual rat brains were input to a trained 1D-CNN. Simulation results confirm that the distribution of the number of chaos generating neurons changes with the growth process. These results are important for a more detailed understanding of how individual neurons producing neuronal signals behave.

2. 1D-CNN Model

A 1D-CNN is used for time series classification by applying convolutional layers directly to sequential data. It processes the input time series by sliding filters over the data, capturing local patterns and temporal dependencies. These learned features are then passed through pooling layers to reduce dimensionality and through fully connected layers for classification. For time series data, a 1D-CNN can effectively learn from patterns and trends within the sequences to classify them into different categories, such as periodic, chaotic, or other types of behavior [9]-[10].

Figure 1 shows the structure of 1D-CNN. The 1D-CNN

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model for time series classification begins with an initial 1D convlutional layer, which applies 64 filters of size 3 to the input data. This layer is responsible for detecting local patterns in the time series, using the ReLU activation function to introduce nonlinearity and help the model learn more complex features. Following this, a max pooling layer is employed, which reduces the dimensionality by selecting the maximum value in each window of size 2. This pooling operation helps to down-sample the data, making the model more efficient while preserving important information.

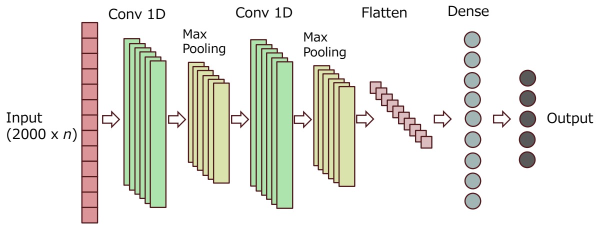


Figure 1: The structure of 1D-CNN for 5 classification.

After the convolutional and pooling layers, the data is flattened into a single vector, which serves as the input to a fully connected layer with 100 neurons. This dense layer allows the model to learn high-level representations from the previously extracted features. Finally, the output layer uses a softmax activation function to produce probabilities corresponding to the different classes (the various chaotic neurons in this case), allowing the model to classify the input time series.

This architecture efficiently combines convolutional layers to capture local features, pooling layers to reduce the dimensionality, and dense layers to make predictions, making it well-suited for time series classification tasks.

3. Data Set Using Izhikevich Neuron Model

This section describes the training data. The training data consists of neuron signals obtained from a coupled Izhikevich neuron model [7], [8]. The Izhikevich neuron model is governed by the following differential equations:

$$\begin{cases} \dfrac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I \\ \dfrac{du}{dt} = a(bv - u) \end{cases} \tag{1}$$

$$\text{if } v \geq 30, \text{mV}, \quad v \leftarrow c, \quad u \leftarrow u + d$$

where, v is the membrane potential (in mV), u is the recovery variable and, I is the external input current. By adjusting the parameters a, b, c, and d, various types of neuron spike trains can be generated.

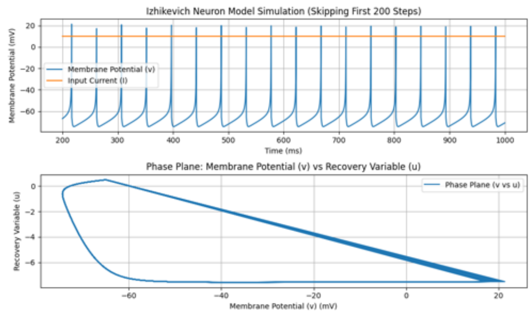


Figure 2: Periodic spiking and attractor. ($a = 0.02, b = 0.2, c = -65$ and $d = 8$).

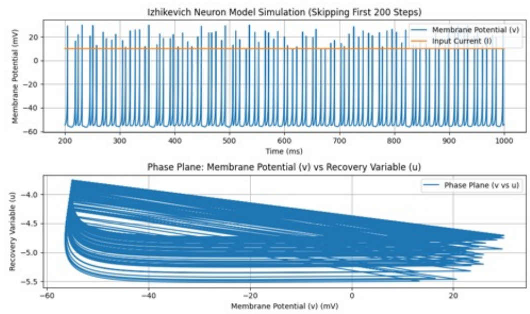


Figure 3: Chaotic spiking and attractor. ($a = 0.02, b = 0.2, c = -55$ and $d = 0.93$).

Figures 2 and 3 show the time series and attractor for periodic spike trains, as well as the chaotic spike trains and their corresponding attractors.

Next, we derive the raster plot by plotting neuron signals from a system of 100 randomly connected Izhikevich neurons when a certain threshold is exceeded. The connection probability for random connections is set to $p = 0.3$. The number of excitatory neurons to inhibitory neurons is set to 80 : 20. The excitatory neurons generating periodic spikes and chaotic spikes is varied (0, 20, 40, 60, and 80). Table I shows the correspondence between the number of chaotic neurons and the names of the respective time series.

Table 1: Name of 5 different time series depending on the number of chaotic neurons.

Number of chaotic neurons	Name
0	0 chaos neuron
20	Few chaos neurons
40	Average chaos neurons
60	Many chaos neurons
80	Full chaos neurons

Figure 4 shows example of time series of spike rate for every chaos neuron numbers (0, 20, 40, 60, and 80). When the number of chaotic neurons is 0 or 20, the time series exhibits periodic behavior. However, by increasing the chaotic neurons, the wave forms become more complex.

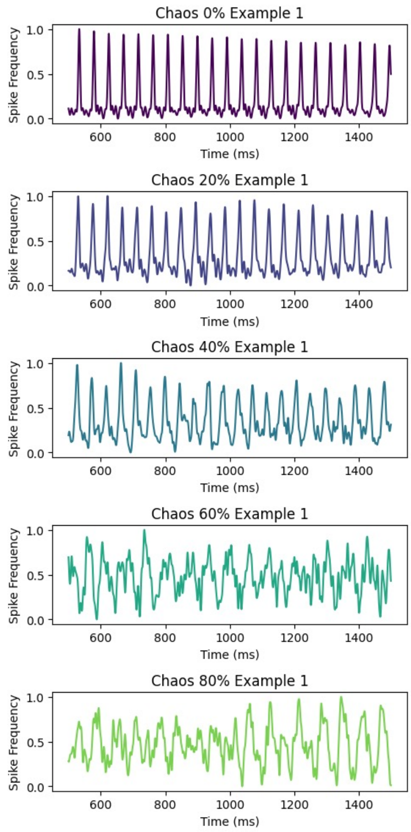


Figure 4: Example of time series of spike rate (chaos neurons: 0, 20, 40, 60, and 80).

4. Simulation Results of Izhikevich Neuron Model

The 1D-CNN was trained on five types of time series, each with different number of chaos neurons. The data length for each time series was 2000 points, and a total of 100 time series were prepared, with 80% used as training data and 20% as validation data. The number of epochs was set to 100, with early stopping enabled upon the completion of training.

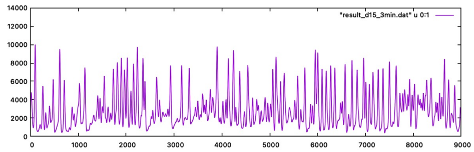
By monitoring the learning and loss curves it is confirmed that the learning of the five different time series works well. We confirmed that the 1D-CNN successfully classified the five types of time series.

5. Applying 1D-CNN for Real Neuron Data

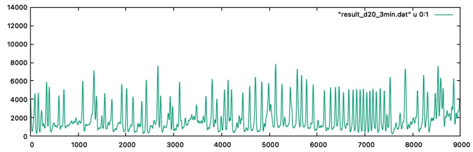
Finally, we examine the results of inputting actual neuronal signals obtained from a Wister rat brain into the trained 1D-CNN. In this section, we will first provide a brief explanation of how the neuronal signals were obtained from the rat brain.

Neuron signals were measured using the MaxOne CMOS-based high-density microelectrode array (HD-MEA) system, which consists of 26,400 platinum electrodes arranged in a grid with a 17.5 μm spacing between them. Up to 1,024 electrodes could be recorded simultaneously using a flexible switch-matrix. The system amplified, filtered, and digitized the signals, and spike detection was performed online using MaxLab Live software. Neuron cultures were prepared from Wistar rat cortices and grown on the electrode array.

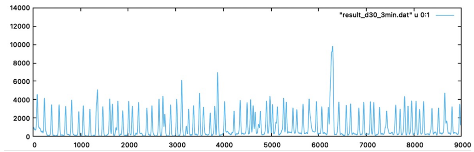
Figure 5 shows the time-series data depending on the spike rate at certain bin. DIV stands for Day in Vitro, where the numbers represent days. In other words, DIV15 means 15 days after the rat brain was picked out.



(a) DIV 15.



(b) DIV 20.



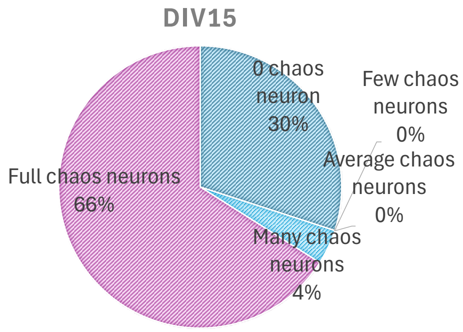
(c) DIV 30.

Figure 5: Time series of spike rate.

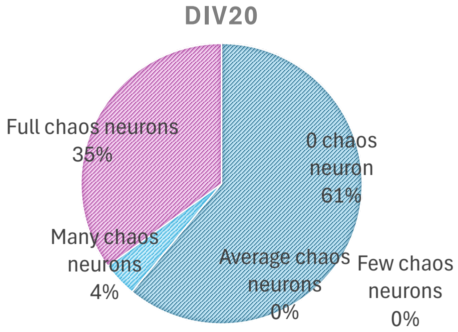
6. Simulation Results of Real Neuron Data

We measured how the trained 1D-CNN classified the neuronal signals from the rat brain at DIV15, 20, and 30, each with 10 time series of 2000 points, in terms of the number of chaos neurons. Figure 6 shows how the distribution of chaos neuron categories changes at three different stages: DIV15, DIV20, and DIV30.

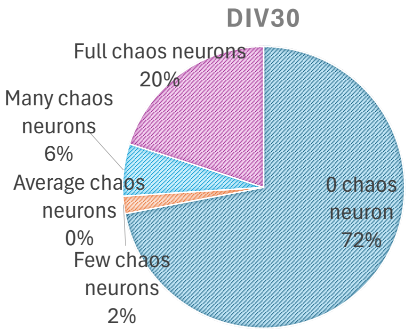
The number of “0 chaos neurons” increases over time, from 30% at DIV15 to 72% at DIV30. The number of “Full chaos neurons” decreases over time, from 66% at DIV15 to 20% at DIV30. These results suggest that as time progresses, the proportion of fully chaotic neurons decreases, while the proportion of periodic neurons increases. This indicates a shift toward more stable neuronal activity over time.



(a) DIV 15.



(b) DIV 20.



(c) DIV 30.

Figure 6: Simulation results.

7. Conclusion

In this study, we investigated how the chaotic characteristics of neuronal signals from the rat brain change during the growth process. First, we generated synthetic time series using the Izhikevich neuron model and constructed a 1D-CNN to classify the time series based on the number of chaotic neurons. Finally, we applied the trained 1D-CNN to real neuronal signals and found that chaotic behavior increases and periodic behavior increases as the organism grows.

Future work includes applying other time series classifiers such as Recurrent Neural Networks or Reservoir Computing and validating the findings using other neuron data.

Acknowledgment

This work was partly supported by JSPS KAKENHI Grant Number JP25K15273.

We would like to express our gratitude to MaxWell Biosystems for providing the real neuron data used in this research. Special thanks to Dr. Urs Frey and Dr. Marie Engelene J. Obien for their invaluable support and collaboration.

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