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Chaotic Data Classification Methods for Residual Neural Network

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Abstract– Chaotic data can be seen in a variety of data, including biological signals. Therefore, there is a need in various fields to study the classification of chaotic data. In chaos theory, there is a method of embedding data using 3D spatial coordinates called attractors. In this study, an attractor image was created using chaotic data, and its classification accuracy was examined using a neural network. In this study, ResNet, one of the neural networks, was used to classify the attractor images of chaotic data. We proposed two types of attractor images: a squared attractor, which devised a way to make the original attractor features more prominent by squaring the original chaotic data values, and an attractor with ve-locity information, which reflects the attractor's velocity information. As a result, it was confirmed that the new attractor image achieves higher classification accuracy than the conventional attractor image.

1. Introduction

Neural networks have attracted a great deal of attention in recent years and have achieved significant results. They are used in a variety of settings, including image recognition, prediction, and language processing. They are also used not only in the academic field but also in the industrial field.

Currently, neural networks are outperforming the Human error rate. This allows neural networks to classify images that are impossible for humans to classify [1]. Research such as biological signal analysis is also conducted using neural networks [2].

ResNet (Residual Neural Networks) [3] is one of the most used neural networks in image classification. It solves the gradient loss problem, which has been a problem in the past by reflecting information from the input in the output. In this study, ResNet was used.

Chaos theory is used to analyze the chaotic data handled in this study. Chaos is a signal that appears to be disordered but is deterministic. Chaos theory is a theory that deals with phenomena in certain dynamical systems that exhibit complex aspects that are considered unpredictable due to numerical errors. Unpredictable does not mean random. It means that the behavior of the system follows deterministic laws, but since the integral method cannot provide a solution, the future, and past behavior must be determined by numerical analysis. However, because of initial value sensitivity (the property that if there is a very small difference in the initial state of the same system, that difference grows exponentially with time), information at a certain point in time must be obtained with infinite precision, and errors in the process of numerical analysis amplify the difference between the value obtained and the true value. In other words, prediction is virtually impossible.

Typical examples of chaotic data include biological signals [4], weather phenomena, and stock price fluctuations. Improving the accuracy of chaotic data classification is expected to make a variety of contributions. Chaotic data classification using atlases reconstructed by neural networks has been studied [5]. Therefore, this research aims to make the characteristics of chaotic attractors more prominent in order to improve the accuracy of chaotic data classification. In addition, the reason why we use chaotic data as attractor images is that it is possible to show the differences in the behavior of the data in a small amount of data in a noticeable way.

There are two types of attractors we propose: the first is called a squared attractor, which is created by squaring all the original attractor data. The second is an attractor that includes velocity information. The conventional attractor can reflect the trajectory of the chaos data, but it cannot reflect the process of the chaos data. Therefore, this attractor allows the attractor to be displayed as a plot. This is to reflect one of the most important pieces of information, the velocity information, in the attractor.

As a result, the two attractors proposed here show higher classification accuracy than the conventional attractor.

2. Residual Neural Network

ResNet (Residual Neural Networks) is one of the most used neural networks in image classification. ResNet is the Winner network of ILSVRC2015. When multilayer neural networks are used in traditional neural networks, there is a problem called the gradient loss problem. This is a problem in which the gradient becomes too small to find the optimal solution, making learning impossible. Therefore, ResNet proposed a method to learn deeper convolutional neural networks (CNNs) by introducing residual blocks and learning residuals. With this mechanism, even with a considerable number of deep convolutional layers (50~150 layers), object recognition CNNs can be trained from large-scale image data as highly accurate models without degradation problems. Figure 1 shows a flowchart of the

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CNN and ResNet. In this study, ResNet50 with 50 intermediate layers is used.

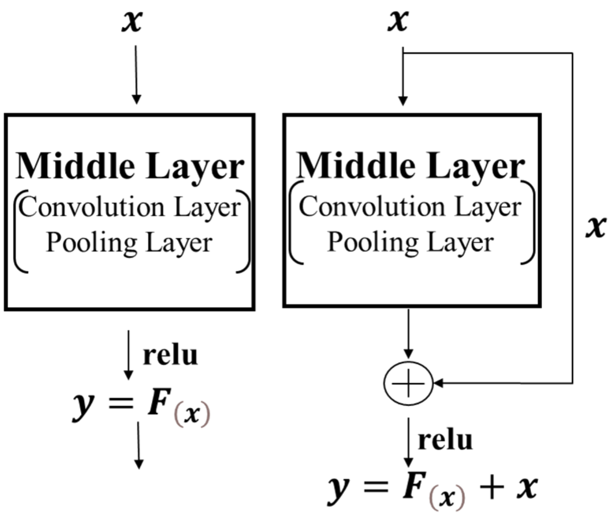

Fig 1: CNN, ResNet.

3. Theorem of Embedding of Takens

Takens' Embedding Theorem can be used to embed $x(t)$ time-series data into a coordinate system with a time difference [6]. Equation (1) shows the Takens' Embedding Theorem. Figure 2 shows 1D data embedded in an attractor.

$$v(t) = \big(x(t), x(t+\tau), \dots, x(t+(n-1)\tau)\big) \qquad (1)$$

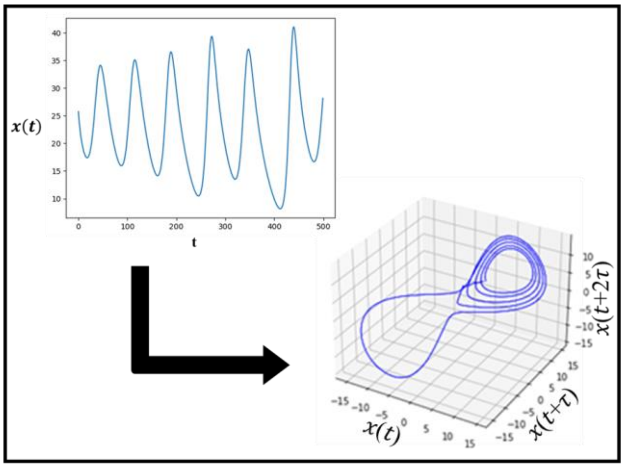

Fig 2: 1D data embedded in an attractor.

4. Data-set

Equation (2) represents the Lorenz equation. It is one of the most famous mathematical models in which chaotic behavior is observed, was used as the chaos data in this study. The three parameters of the Lorenz equation, σ, β, and ρ were set to 27, 28, and 29 for the ρ parameter, and the data were divided into three parts. The reason for setting these values was to perform a high-difficulty classification. The chaotic nature of the data was confirmed at ρ =28. A high difficulty data set was created by selecting ρ =27 and 29, which do not show a clear difference from ρ =28. The initial values of X, Y, and Z were set from 1.0 to 2.0 in increments of 0.1. For each combination, 1000 data were set; 3000 data were created for the three types of ρ. These were divided into 1800 training data and 1200 test data. Figures 3, 4 and 5 show some of the three types of data for different P. Equation 2 below shows the Lorenz equation. (σ=10, β=8/3, ρ=27. 28. 29)

$$\begin{cases} \dfrac{dx}{dt} = \sigma(y - x) \\ \dfrac{dy}{dt} = x(\rho - z) - y \\ \dfrac{dz}{dt} = xy - \beta z \end{cases} \qquad (2)$$

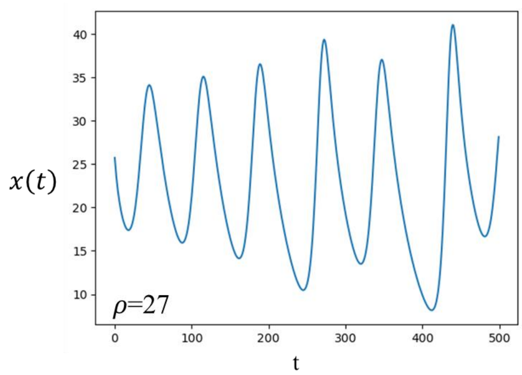

Fig 3: Part of Lorenz data (ρ =27).

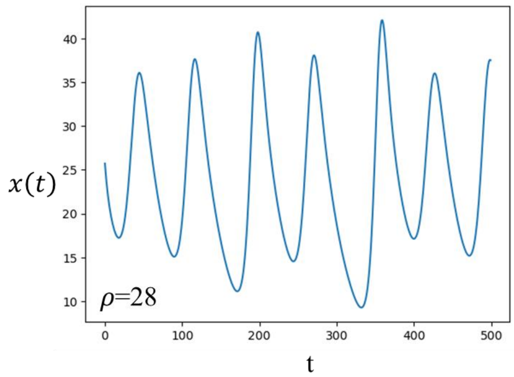

Fig 4: Part of Lorenz data (ρ =28).

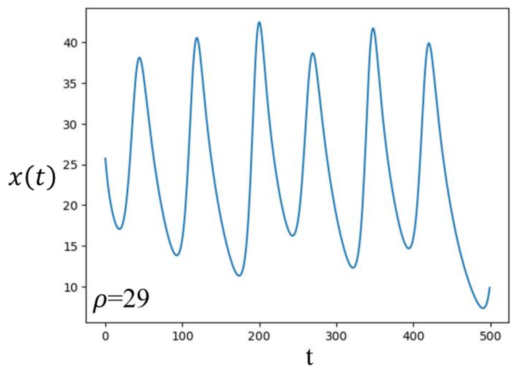

Fig 5: Part of Lorenz data (ρ =29).

5. Proposed Attractor

Figures 6, 7, and 8 show some of the data from the traditional attractor image and proposed attractor image. Figure 6 shows the traditional attractor with the chaotic data unmodified by applying Takens' embedding theorem. Figure 7 shows the squared attractor designed by squaring all the original data values proposed in this study. Figure 8 shows the attractor with velocity information added to the trajectory drawn by the attractor proposed in this study. the reason why the shape of the squared attractor is significantly different from the traditional attractor is that the negative elements of the data are replaced by positive ones. The reason why the color of the attractor with velocity information differs from place to place is due to the plot settings. The color of the attractor is designed to be darker at points where the plotting speed is slow.

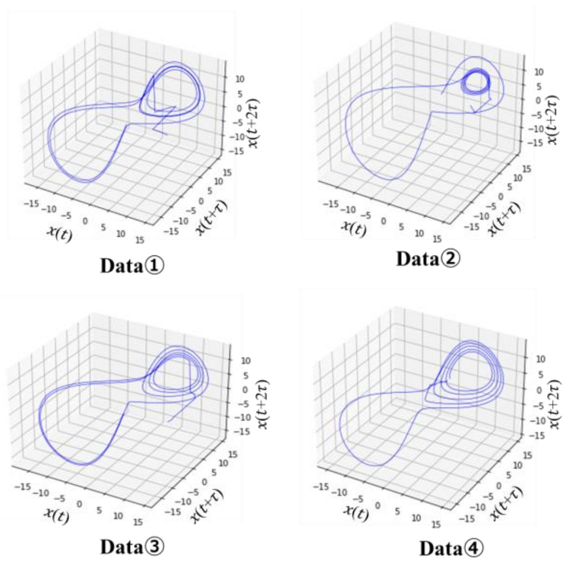

Fig 6: Traditional attractor.

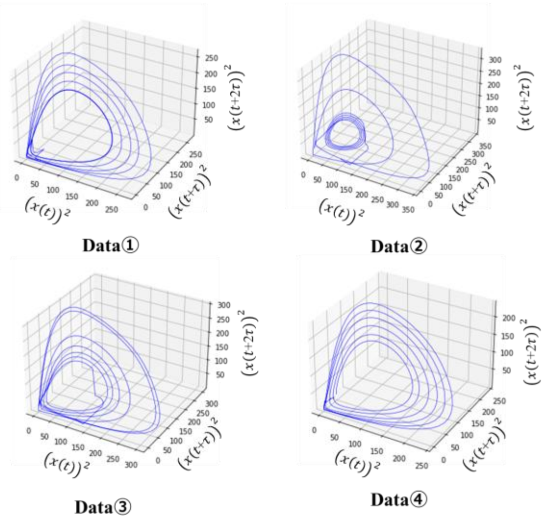

Fig 7: Proposed attractor (squared attractor).

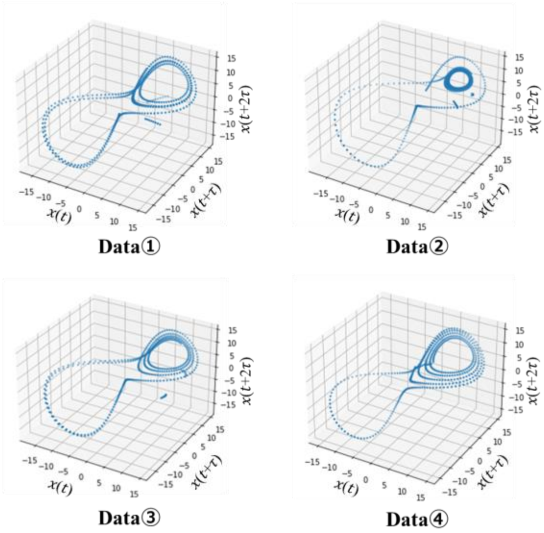

Fig 8: Proposed attractor (includes speed information).

6. Simulation Conditions and Results

This section presents the simulation conditions and results. Table 1 summarizes the simulation conditions. Table 2 shows the simulation results of classification accuracy for the traditional attractor and the two attractors proposed in this study. The simulation is terminated this time when there is no decay in test accuracy during 150 epochs. As a result, the squared attractor is 13% more accurate than the previous one, and the attractor with speed information is 8% more accurate than the previous one.

Table 1: Simulation Conditions

Condition Item	Application
Batch sizes	16
Epoch	300
Optimizations	Adam
Initial value of learning coefficients	0.0001
Minimum value of learning coefficients	5.0×10^{-7}

Table 2: Simulation Results

attractor	Classification accuracy (%)
traditional Attractor	71.2
Squared attractor	84.3
Attractor with speed information	79.8

7. Consideration

This section discusses why the attractor images proposed in this study show better classification accuracy than traditional attractor images. First, a discussion of the squared attractor is presented. Figures 9 to 12 show a comparison of the proposed attractor with the traditional attractor. As can be seen from all the figures, the squared attractor has a wider line spacing than the traditional attractor. From this, it can be said that we have succeeded in showing the features of the attractor more prominently. As a result, we believe that the feature extraction of attractor images has become easier, leading to improved classification accuracy. Second, we present a consideration of attractors with velocity information. As can be seen from all of Fig. 9-12, the velocity information of the chaotic data, which has not been shown by traditional attractors, can be shown by displaying the attractor as a plot. In addition, it can be confirmed that the trajectory of the attractor is darker at locations where the velocity is slow due to the plot settings. From the above points, we have succeeded in showing the velocity information, which is one of the important elements of the data that has not been reflected by the traditional attractor, in attractor. As a result, the classification accuracy was improved. The two attractor images proposed in this study were shown to be superior to traditional attractor images.

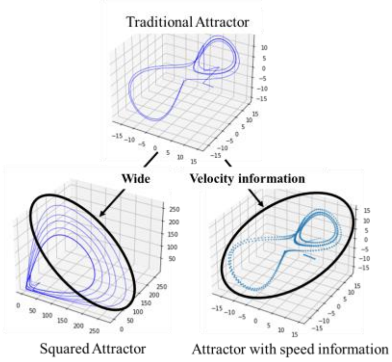

Fig 9: Attractor (Data①).

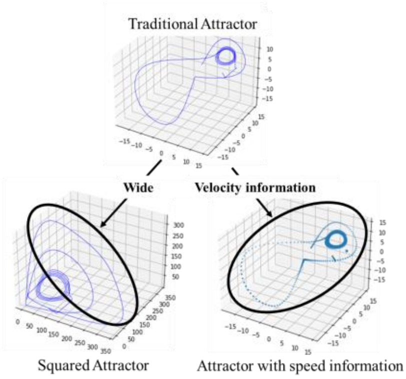

Fig 10: Attractor (Data②).

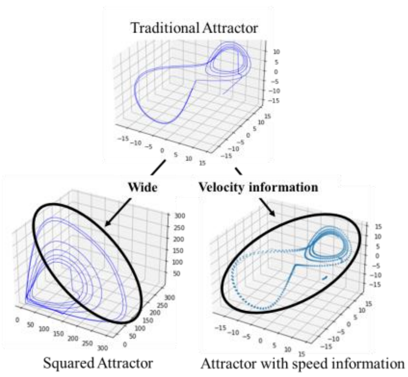

Fig 11: Attractor (Data③).

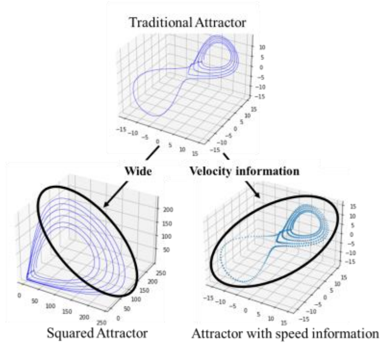

Fig 12: Attractor (Data④).

8. Conclusion

The objective of this study was to obtain highly accurate results by using the proposed attractor image to classify chaotic data. Two attractors were proposed: a squared attractor designed by squaring the original attractor data and an attractor reflecting velocity information on the original attractor. As a result, both two proposed attractors showed more accurate classification results than those obtained using the traditional attractor.

References

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