令和2年度電気·電子·情報関係学会四国支部連合大会 講演論文集 (愛媛大学)
2020 SHIKOKU-SECTION JOINT CONVENTION RECORD OF THE INSTITUTES OF ELECTRICAL AND RELATED ENGINEERS (EHIME UNIV.)

Chaotic Time Series Analysis Using Multidimensional Attractors with Neural Network

Tomoya Takata Yoko Uwate Yoshifumi Nishio
(Tokushima University)

1. Introduction

It is difficult to analyze unpredictable time series data using Neural Network (NN). Therefore, it is important to search for the effective features of the data. In this study, we transform the dimension number of the data and refer to features suitable for NN classification. We investigate how the features of the multidimensionally expanded data should be extracted.

2. Proposed Method

In this study, we propose a method of feature translation for using multidimensional features of time series data (Fig .1).

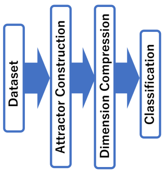

Figure 1: Feature translation.

Attractors are constructed by converting 1-Dimensional data (1D-data) into multidimensional data using time delay embedding. $x(n)$ is the amplitude at a certain time. Equation (1) represents this system with the time delay value τ.

$$f(x) = [\ x(n)\ x(n+\tau)\ x(n+2\tau)\ ...] \quad (1)$$

In this study, the dimensional compression methods which are (a) Isomap and (b) Kernel Principle Component Analysis (Kernel PCA) are used. Isomap is a method that uses the geodesic distance of multidimensional data. Kernel PCA is a method of multivariate analysis that synthesizes variables called principal components. The procedures of the methods are shown in the following steps:

(a) Isomap

step 0. Determine the neighbors of each point.

step 1. Construct a neighborhood graph.

step 2. Compute shortest path between two nodes.

step 3. Compute lower-dimensional embedding.

(b) Kernel PCA

step 0. Convert the original data into the gram matrix using kernel method.

step 1. Calculate the covariance matrix of the gram matrix.

step 2. Perform eigenvalue decomposition on the covariance matrix.

step 3. Project the data to the space of eigenvectors for lower-dimensional embedding.

3. Simulation Result

In this study, chaotic time series data which composed of the X-axis value of Lorenz Equation in Eq. (2) are used as input. Lorenz equation is solved by the Runge-Kutta method.

$$f(x) = \begin{cases} \frac{dx}{dt} = -px + py \\ \frac{dy}{dt} = -xz + rx - y \\ \frac{dz}{dt} = xy - bz \end{cases} \quad (2)$$

In this study, three datasets are created by changing the parameter value of r. Table 1 shows the number of the data with the 1000 points.

Table 1: The number of the time series data.

data	r=28	r=29	r=30
train data	300	300	300
test data	60	60	60

Table 2 and 3 show the test accuracy of the conventional and the proposed methods using 1D-CNN. By setting the learning rate to 0.001 and the epoch of the training to 20, the training accuracy has reached a maximum value of 1.000. Test accuracy is calculated by averaging of 10 times.

The test accuracy of applying Isomap to the 5D-data is the best, and that of applying Kernel PCA to the 5D-data is the worst. It can be said that the features of the data have changed significantly when converting the original data into the 5D-data.

Table 2: Test accuracy of the conventional method.

original	0.566

Table 3: Test accuracy of the proposed method.

	3D	4D	5D
Isomap	0.572	0.572	0.646
Kernel PCA	0.598	0.599	0.523

4. Conclusion

In this study, the influence of the input features into accuracy is observed in each dimension. However, the origin of the accuracy flactuation remains unclear.

In the future, it is necessary to investigate which dimensional compression method should be applied to which dimensional data.