Investigation of the Effect of Adding Random Noise to Noisy Biological Signals on the Classification of Neural Network

Ryosuke Shimizu, Yoko Uwate and Yoshifumi Nishio
Dept. of Electrical and Electronic Engineering, Tokushima University
2-1 Minami-Josanjima, Tokushima 770--8506, Japan
Email:{shimizu, uwate, nishio}@ee.tokushima-u.ac.jp

Abstract— **Time series classification is an important and challenging problem in data analysis. Recently, time series analysis using neural networks (NN) has attracted much attention. However, the analysis of noisy time series data with complex oscillations is difficult. Therefore, it is important to search for effective features of the data. In this study, we add the data to the noise and search for features suitable for NN classification.**

Keywords; Neural Network,Time series Classification

I. INTRODUCTION

In recent years, there has been a lot of research on time-series data analysis using neural networks (NN). The results show that it is difficult to classify noisy data with NN. Therefore, data preprocessing is important in NN. To solve this problem, this study generates randomly varying noise. The signal-to-noise ratio of the noise is adjusted and added to the biological signal. The signals to which the noise is added are then classified using NN. The goal is to find features in the time-series data with complex oscillations that are easy for the NN to learn the waveform.

II. CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Network (CNN) is one of the NN and is mainly used in image recognition [1]. CNN is a model with a hierarchical structure that overlaps layers called convolutional layers, and the accuracy has been improved by deepening this hierarchical structure. In the 2015 competition, the Residual Network (ResNet) layered 152 layers and won the competition of the year. Now ResNet is popular as one of the standard CNN models [2].

III. DATASET

The data from the UCR repository [3] used in this study is an electromyogram (EMG) of hand movements. Five healthy subjects (two males and three females) of approximately the same age (20 to 22 years old) are asked to repeat the following six movements that are considered to be basic hand movements used in Fig. 2 [4]. An example of EMG time series data is shown in (Fig. 3).

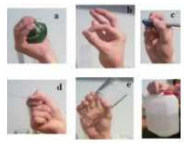

Figure 1. Image of Six hand movements.

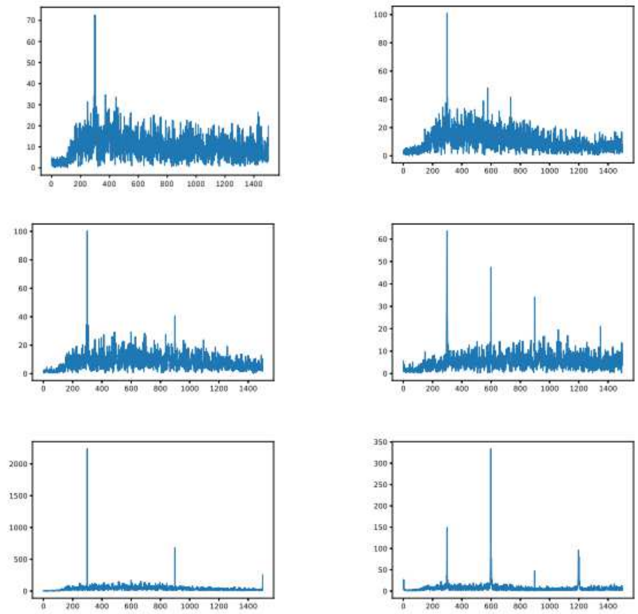

Figure 2. Waveform of Six hand movements.

IV. PROPOSED METHOD

In this study, we propose a method of feature translation for using multidimensional features of time series data. Figure 3 shows the flow of the proposed method of this study.

① The randomly varying noise is generated.

② The signal-to-noise ratio is adjusted and noise is added to the data.

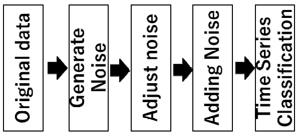

Figure 3. Proposed method.

A) The Signal-to-Noise Ratio

The SN ratio formula is used to find the RMS of noise that will give an arbitrary signal-to-noise ratio for speech. The RMS of the noise to be obtained can be obtained by transforming Eq. (1) and using Eq. (2). The ratio of the RMS(N_{noise}) calculated in Eq. (2) to the RMS of the original noise is calculated, and the amplitude of the original noise is adjusted by that ratio. Then add the amplitude of the adjusted noise and the amplitude of the original data.

$$SNR_{db} = 20\log_{10}\frac{S_{signal}}{N_{noise}} \tag{1}$$

$$N_{noise} = \frac{S_{signal}}{10^{\frac{SNR_{db}}{20}}} \tag{2}$$

V. SIMURATION MODEL

In this study, the 1d-ResNet is used for classification model.

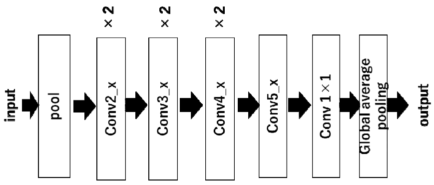

Figure 4. 1d-ResNet structure used in this study.

ResNet is commonly used for the classification of image data. ResNet is the winner network of ILSVRC 2015, and it is the network that enable to have deep layered networks without vanishing gradient problem by using residual learning that is shown in Fig. 6. By inserting the shortcut connection that is expressed by the longest arrow over 3 convolutional layers, previous information is learned, and it avoid vanishing gradient problem. In Fig. 5 and the following Fig. 6, Convolution (1×1, 128) indicates convolution layer with 1×1 filter and 128 channel.

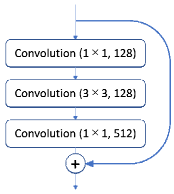

Figure 5. The structure of residual learning.

Table I shows the batch size, epochs, and learning rate in this study. Batch size is the amount of data processed at once. The epoch is the number of the learnings. Simulation terminates when val loss no longer decays during 1500 epochs. The learning rate is the degree of learning progress. By setting as shown in Table I, the training accuracies reach 100%.

TABLE I. LEARNING PARAMETERS.

	Batch size	***Learning rate***	***Epoch***
1d-ResNet	42	0.0001	Early stopping

VI. SIMULATION RESULTS

We investigate the average of 5 times of test accuracy. 1d-ResNet is used to investigate the accuracy of 6-value classification. Table Ⅱ shows the test accuracy of the original data and the highest and lowest accuracy of data by the proposed method. Although there are outliers, the accuracy depends on the magnitude of the noise. The results also show that there is an optimal value for NN depending on the magnitude of the signal-to-noise ratio. It was also found that there is an optimal value for NN depending on the amplitude of the signal-to-noise ratio in Fig. 6.

TABLE II. LEARNING PARAMETERS

	Test accuracy
original	0.841
SN=10	0.871
SN=1	0.806

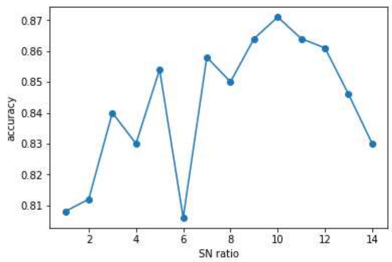

Figure 6. Accuracy of proposed method.

VII. CONCLUSION

In this study, we checked how the accuracy of time series classification by 1d-ResNet changes when noise is added to noisy data. The results showed that the accuracy increased with the size of the noise. We would like to investigate how the accuracy changes when various types of noise are added.

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