Evaluation of Time Domain and Frequency Domain Classification Ability in Acceleration Tactile Signals

Masahiro Koga[1], Satoshi Saga[1], Shotaro Agatsuma[2], Junya Kurogi[1] and Tsuyoshi Usagawa[1]

***Abstract*— Our previous studies have shown that CNN can classify time domain signals of acceleration tactile signals. In this research, we aim to evaluate time domain and frequency domain classification ability, dependency on input signal length in acceleration tactile signal through an experiment.**

The Experimental results show that the accuracy tends to increase as the data length increases in time domain signals. In frequency domain signals, there was a problem that learning did not progress if the hyper parameters of the model were not changed. Further this classification accuracy with advanced learning tended to stop at about 50 - 60%. In 1k Hz sampled both domain signals, it was found that classification is possible for 5 classes. Also in this data, it was found that the accuracy tends to improve in proportion to the data length.

I. INTRODUCTION

In recent years, with the spread of tactile displays, much research has been done on systems that collect information. The collected information is mainly applied to the output of tactile displays. In addition, many attempts have been made to classify the collected information in order to provide an appropriate tactile presentation on the displays.

In previous researches [1] [2], they have developed a dedicated device that combines various sensors to collect tactile information. In these methods, these researches collected tactile information under a limited experimental environment, in daily activities. To solve this problem our research group does not use integrated tactile sensors to detect tactile information. We have proposed a method to collect information easily [3].

In this proposed method, the tactile information is limited to the acceleration information only. Furthermore, we have shown that it is possible to classify texture information by collecting accelerations of tactile motions on a desk and performing machine learning using a convolutional neural network (CNN). Machine learning using CNN has succeeded in classifying 30 types of data at approximately 90%.

In the previous research, signal data was processed without processing, that is, classification was performed by inputting as a time series signal, but it became necessary to investigate how the classification accuracy changes in different conditions or different processing procedures. Therefore, in this paper, we investigated classification ability between time domain and frequency domain, dependency on input signal length in acceleration tactile signal through an experiment. Furthermore, we investigated how the accuracy changes with the sampling frequencies.

[1]Masahiro Koga, Satoshi Saga , Junya Kurogi and Tsuyoshi Usagawa, Kumamoto University, 2-39-1, Kurokami, Chuo-ku, Kumamoto Japan, [2]Shotaro Agatsuma, University of Tsukuba, 1-1-1, Tennodai, Tsukuba, Japan

II. EXPERIMENT SETUP

The experiment conditions set for conducting the investigation will be described. In this Experiment, data to be input to CNN is set as shown in the following table I.

TABLE I
EXPERIMENT SETTINGS

Data type	Raw data, FFT data			
Sampling Freqency rate	330 Hz		1k Hz	
Data length	128	256	128	256
	512	800	512	1024

This time, we name data obtained from the sensor module “raw data”, and a Fast Fourier Transform (FFT) amplitude spectrogram of raw data “FFT data”.

Regarding model input, 3ch with x, y, and z axes data obtained from the acceleration sensor is used as input, and the classification accuracy in the case of changing the input data length is evaluated. The NN used this time is a model based on the Convolutional Neural Network (CNN). This model is an improvement based on VGG 16 [5] and uses parameters adapted to input data. A schematic diagram of the basic model of this CNN is shown in the following Fig. 1.

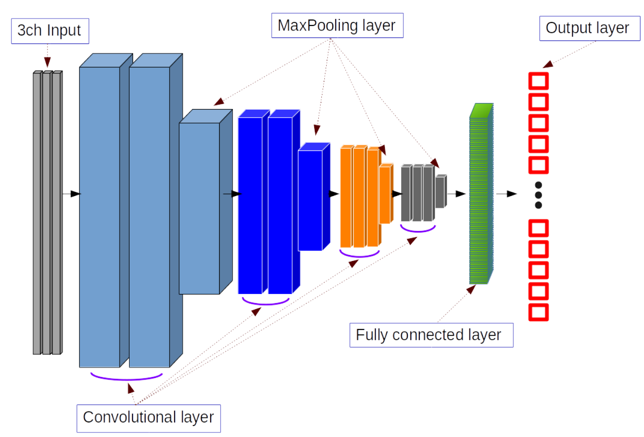

Fig. 1. Basic CNN model in this research. In this research, this model is used as a basic model, and the input size, the number of output features of the convolutional layer, and the number of layers of the convolutional layer are adjusted to advance learning for the input data.

The additional operation of bias and the activation processing by the LeakyReLU function are performed for each block in Fig. 1. Moreover, the softmax function was used for the activation function of the output layer, and the loss function used the cross entropy error. We used Adam Optimizer [6] as the optimization algorithm for learning, repeated learning until the training accuracy converged, and then evaluated the accuracy of the test data.

HOW TO EXPERIMENT

In this experiment, the data set is divided into $training : test = 8 : 2$ and the CNN model is trained using the training data set. Using training data, measure the accuracy of the learned model with test data. The batch size of test input is 32 and accuracy is given for each batch. The test is performed 10 times, and the maximum, minimum and average accuracy among them are calculated to evaluate the model.

III. Result of Experiment

Results of 330 Hz sampling data

The following Fig. 2 shows the accuracy when changing the input data length in raw data and FFT data. As data used at this time, 32 out of 300 prepared test data groups were randomly used. The accuracy of the minimum-maximum value when this is repeated 10 times is shown.

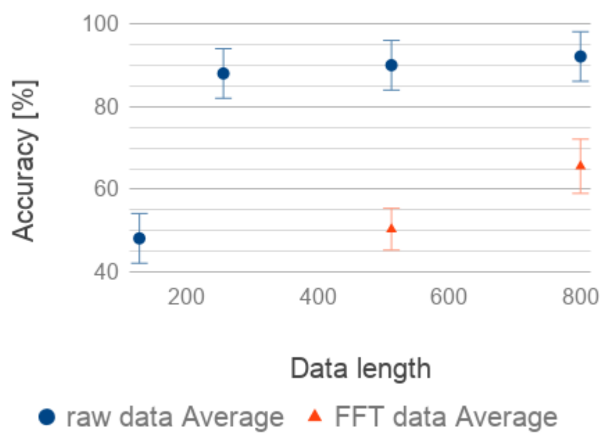

Fig. 2. Test accuracy average and standard deviation of 330 Hz data

Results of 1k Hz sampling data

The following Fig. 3 shows the accuracy when 1k Hz sampling raw data and FFT data are changed in the input data length. As data used at this time, 32 out of 120 prepared test data groups were randomly used. The accuracy of the minimum-maximum-average is shown when this is repeated 10 times.

IV. CONSIDERATION

This experimental result shows that it can be seen that features can be found from the time domain and the frequency domain since the chance level is clearly exceeded in any case. In addition, the accuracy tended to be monotonically increasing to the data length. This tendency was observed in

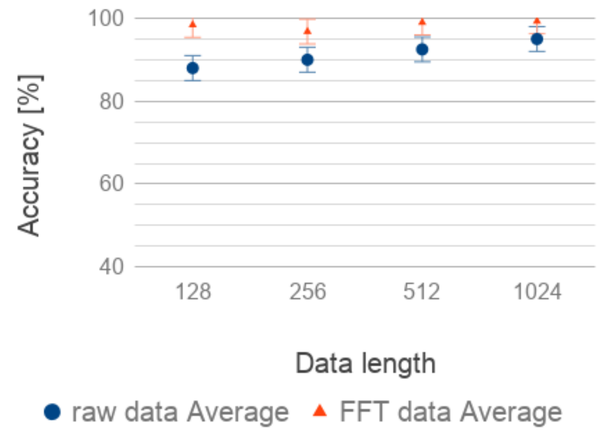

Fig. 3. Test accuracy average and standard deviation of 1k Hz data

both time domain data and frequency domain data. In the classification of 330 Hz data, when the data length is 128, the accuracy is low compared to other data lengths, and the small amount of information suggests

that CNN may not have been able to capture features. However, further problems were found in this survey, such as the setting of hyper-parameters and issues with a different number of classes of 1 k Hz data.

V. CONCLUTION AND FUTURE WORK

In this experiment, the number of classes are 30 classes for 330 Hz data and 5 classes 1k Hz data. Thus , the effect of the sampling frequency was not correctly evaluated. However, when the time domain data and the frequency domain data are compared at the same sampling frequency, the frequency domain data is accurate, so that the frequency resolution may be increased by the increase of the sampling frequency, and the signal feature may be easily grasped. As a future work, we plan to investigate the control effect of hyperparameters of CNN model since there is a possibility that the accuracy may change by optimization.

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