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Gesture Machine Learning and Recognition Rate Change using Multi Class Classification

[1]JangYeol Lee, [2]Earl Kim, [3]ChoonSung Nam, [4]DongRyeol Shin
[1][2][3][4] Department of Electrical and Computer Engineering, Sungkyunkwan University

***Abstract* - The contact type gesture acquisition method is a method of specifying the threshold value and recognizing the gesture when the threshold value is exceeded. Since this method does not take into account other conditions depending on gender, age, and height, it is a problem of lowering the recognition rate when using the specified threshold value. In addition, the Threshold method can not guarantee the scalability of the Gesture because it has a limitation to add the operation of Gesture. In this paper, we apply the machine learning to the gesture to solve the problem of the existing threshold method and examine the recognition rate. We classify three gestures (rock-scissor-paper) obtained by contact device using multi class classification algorithm and conduct experiment to improve recognition rate. We perform three experiments to understand recognition rate improvement. First, we examine the recognition rate change according to the learning dataset size. Second, we examine the recognition rate when some sections of gesture data are learned and finally the recognition rate when smoothing is applied to gesture data. The results show that the recognition rate increases as the feature value of the gesture data becomes clearer, and the recognition rate of the gesture increases from 63% to 97%.**

Index Terms: machine learning, multi class classification, gesture recognition rate, section of gesture.

I. INTRODUCTION

Recently, researches and developments have been actively carried out for interactions with motion recognition technology in services such as drones control and IoT based smart home control. The technology types of the motion recognition based user interface can be classified into contact type and non-contact type. The contact type is a method of using gesture data acquired by a device, and the non-contact type is a method of acquiring gesture data of a user using a video device such as a camera. A major problem of non-contact type motion recognition is that it must be a camera that detects motion, and it is a place limitation problem that can be recognized only in a place where the camera can shoot. This is a great inconvenience in operating a mutually operating device since it is possible to recognize the operation only at a designated position where the camera is installed. Contact motion recognition technology is one way to overcome the limited problem of non-contact motion recognition. However, contact motion recognition has the problem that motion triggers operate freely when the motion trigger is not desired. This is because the threshold value set in the contact device is preset and the operation is recognized when the threshold value is exceeded. In such a method, EMG (electromyography) values are different depending on gender, age, and height, so that a large difference in recognition rate may occur. Also, if we recognize the gesture using the threshold value, we can use only the limited gesture. In other words, it is not scalable to various gestures[1][2].

Machine learning is a concept that gives computers the ability to learn on their own without an explicit program[3]. In this paper, we propose a method to recognize motion using machine learning in order to guarantee the problem of recognition rate and extensibility of gesture which is a problem of contact type motion recognition. We also use machine learning to find ways to increase the recognition rate of gesture through three experiments. The three experimental types examine the recognition rate change according to the gesture dataset size, then the recognition rate when extracting a section of the gesture data and finally the recognition rate when the gesture data is smoothed. We use multi class classification as an algorithm for machine recognition learning.

The composition of this paper is as follows. In Section 2, we examine the framework for machine learning and the multi-class classification algorithm used in experiments. In Section 3, we examine three experiments to improve the recognition rate of tools and gestures used in experiments. In the final Section, we conclude with a discussion of the experimental results.

II. RELATED WORK

A. Hadoop

Hadoop is a Java-based open source framework that can easily distribute and process large

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amounts of data across multiple computers. The configuration of Hadoop consists of MapReduce and HDFS (Hadoop Distributed File System).

MapReduce, like Figure1, maps distributed data into key-value pairs and sends them to the Map function as input values. In the map, output the value to be analyzed with the key-value list, remove redundant data, and proceed with the Reduce step to extract the desired data.

As shown in Figure 2, HDFS consists of three nodes: a Name Node, a Secondary Name Node, and a Data Node. The Name Node stores information such as the meta-data and directory structure of the data stored in the File System, and the actual data is stored in each distributed Data Node[4]. If the Name Node fails, the files stored on the Data Node can no longer be retrieved. The Secondary Name Node is operated in case the Name Node fails. The Secondary Name Node is backed up with all the information on the Name Node.

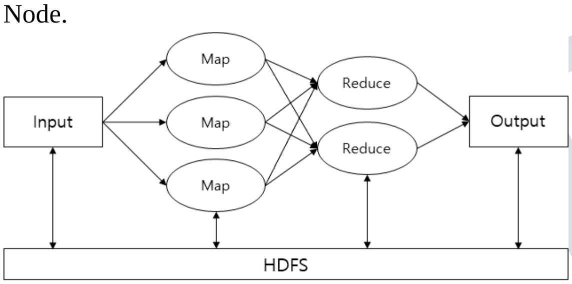

Figure 1 MapReduce

Since the information in the Name Node is also maintained in the Secondary Name Node, even if the Name Node fails, the Secondary Name Node performs the function instead and solves the problem of data I/O. In the data node, one large data is divided into several blocks and stored. The basic block unit is set to 64 Mbytes. In response to one or more Data Node failures, each block is replicated and stored on a different Data Node. Data Node and Name Node communicate periodically, and each Data Node transmits information about the file block being stored to the Name Node.

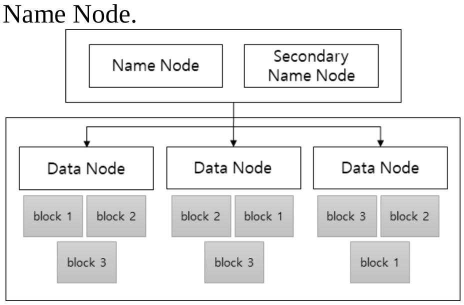

Figure 2 HDFS structure

B. Apache Spark

Apache Spark is a high-performance, general-purpose distributed clustering platform that can perform operations on distributed nodes, Because of the in-memory computing approach, MapReduce speed is up to 100 times faster than disk-based hadoop[5]. In addition to MapReduce, Spark supports streaming data handling, SQL-based data query, machine learning, and supports a variety of languages such as JAVA, R, Scala, and Python.

Figure 3 shows the stack structure of the Apache Spark. At the infrastructure level, it is a Standalone scheduler for spark activation, YARN, Mesos, and Spark is a memory-based distributed cluster environment, so the Spark Core rises to above the infrastructure layer. Spark has four sub-modules: Spark SQL, Spark Streaming, MLlib, and GraphX. The four sub-modules are interoperable with each other, which enhances ease of data processing and analysis. Spark SQL can quickly execute and process Reduce work using Query statement, and Spark Streaming can process real-time data coming from external source in streaming form. MLlib provides various libraries for machine learning in spark, and GraphX supports graph data processing.

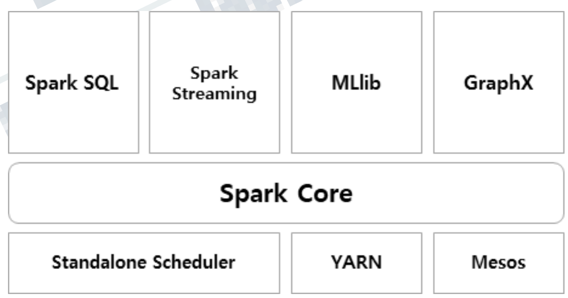

Figure 3 Apache spark stack

C. Multi class classification

One-vs-All (or One-vs-Rest) is a method that can perform multi class classification if binary classification is given. Takes an instance of Classifier and creates a binary classification for each k class. The classifier for class k is trained to distinguish class k from all other classes by predicting whether the label is k. Figure 4 shows One-vs-All using SVM. Given three classes, create all binary classifiers that distinguish each class.

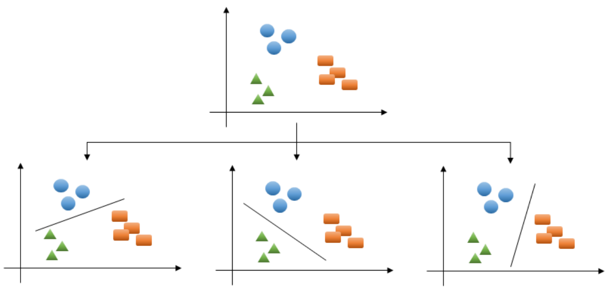

Figure 4 One-vs-All when SVM is given

Prediction of input data is done by evaluating each binary classifier and output as index label of the most reliable classifier.

III. EXPERIMENTAL TOOLS

1) we use the MYO gesture control armband for obtain contact motion recognition data. The MYO is a band-shaped device that allows communication with the computer through only the movement of the arm. The eight built-in sensors in the armband recognize the movement of the human muscles and the exhibit activity and enter it into the computer. On the right side of Figure 5, there are 8 EMG data obtained from MYO. The change in each sensor is characterized by its motion. The figure on the left shows 8 data combined. The section with almost no change up to 150 ms has no motion, and 150 ~ 250 ms is the graph from the moment the gesture progresses until the completion.

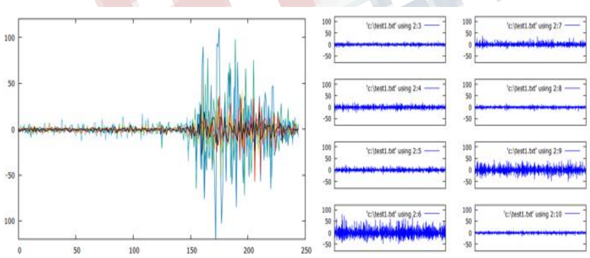

Figure 5 EMG data obtained from MYO

2) we use apache spark as a framework for machine learning gesture data. Apache spark has mllib as a sub-module for machine learning, and mllib provides various libraries for machine learning. Among the libraries provided by mllib, classify gestures by a specified class using multi class classification.

IV. EXPERIMENTAL METHOD

To determine the recognition rate of gestures, we generate and classify three gesture (rock-scissor-paper) data. Using multi-class classification, we examine recognition rate change according to gesture dataset size. Then, the recognition rate when the section of gesture data is extracted and the recognition rate when the gesture data is smoothed is evaluated. Through three experiments, we find a way to maximize the recognition rate for gestures
.

A. Recognition Rate by Gesture Size

Collect the gesture data using the MYO device and set the gesture interval for machine learning. Figure 6 shows a graph of the gesture data obtained from the MYO device. The left figure shows all the data from the Rest to the completion of the motion. Except for the Rest section, the gesture from the start to the completion of motion is cut out and used for machine learning.

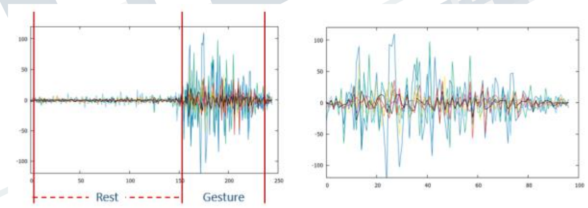

Figure 6 Gesture section for machine learning

Dataset generates about 218Kbyte of data when it performs 20 times of rock-scissor-paper. In order to Inquire recognition rate according to dataset size, machine learning of multi class classification method is performed by making gesture data of 218Kbyte, 1Mbyte and 10Mbyte. 70% of the dataset is used for the training, 30% is used for the test data for the recognition rate evaluation, and the machine learning for each dataset is performed 10 times.

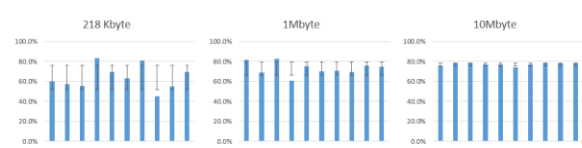

Figure 7 Gesture recognition rate and standard deviation according to dataset

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Figure 7 shows the gesture recognition rate according to dataset size. In the machine learning using multi class classification, the average recognition rate of the 218Kbyte dataset is 63.86% and the standard deviation is 11.37. In the 1Mbyte dataset, the average recognition rate is 72.91% and the standard deviation is 6.22. Finally, the recognition rate of the 10Mbyte dataset is 77.15% and the standard deviation is 1.39. According to gesture dataset size shows the increase in recognition rate and the decrease in standard deviation. However, the increase in recognition rate is not high, and it is inefficient to make a 10Mbyte gesture dataset for recognition rate of about 77%.

B. Recognition rate according to section of gesture

In order to overcome the problem of low recognition rate of the previous experiment, some sections of the gesture are extracted and machine learning is performed in the same way. Figure 8 shows the section of gesture required for learning in the entire gesture data. Based on the peak point at which the gesture is completed, the previous N data are extracted and used for machine learning. The peak point sets the moment when the rock-scissor-paper gesture is completed. In this experiment, the number of data of N = 20 is extracted based on the peak point. (When N = 20, eight EMG data are collected and 160 data of one gesture are collected).

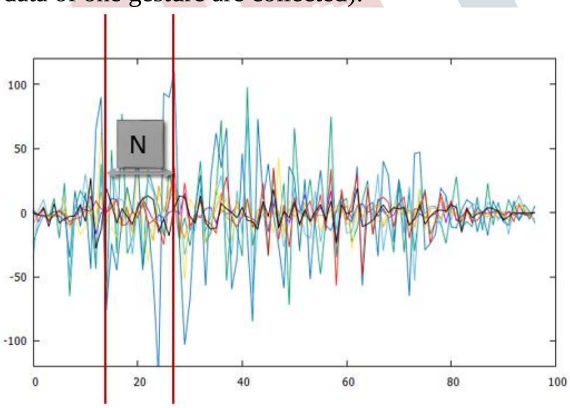

Figure 8 Section to cut gesture

The data generated for this experiment uses a 715kbyte gesture dataset. As in the recognition rate experiment according to Dataset size, 70% of the dataset is used for the training, and the remaining 30% is used for the recognition rate evaluation. As in the previous experiment, machine learning is performed 10 times. Figure 9 shows the results of the 715Kbyte section of gesture dataset. The average recognition rate of learning results is 83.48% and the standard deviation is 2.49.

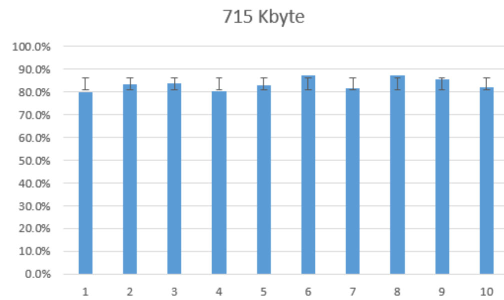

Figure 9 Recognition rate and standard deviation of section of gesture dataset

Compared to the 715Kbyte section of gesute dataset and the previous experiment's 10Mbyte dataset, the standard deviation is 1.1 (2.49-1.39) higher, but the recognition rate of gesture is higher, from 77.15% to 83.48%. The smaller the dataset size, the higher the average recognition rate. The section of gesture has a higher recognition rate than the gesture of the whole section because the characteristics of each other are clearer.

C. Recognition Rate by Gesture Size

Bezier Curve Smoothing is applied to improve the recognition rate by making the feature value of the gesture clearer. Figure 10 shows the graph of the gesture when the Bezier Curve is applied. The graph of the gesture data with smoothing is more distinct than the graph of the gesture data used in the previous experiment.

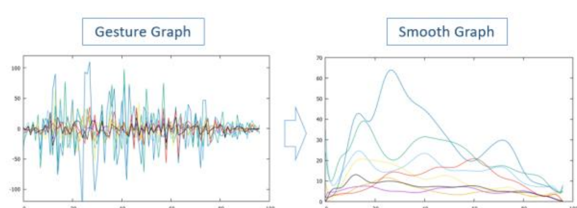

Figure 10 Graph of gesture with Bezier Curve Smoothing applied

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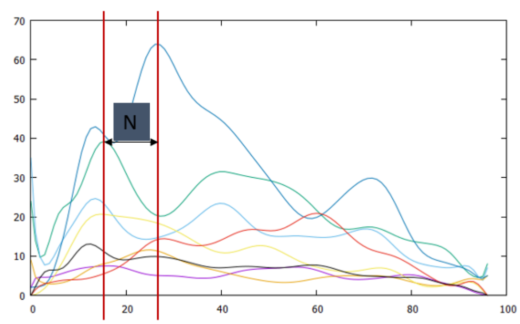

Figure 11 In the graph with Bezier Curve Smoothing applied, section of gesture

Extract the gesture interval as shown in Figure 11. The gesture data with Bezier Curve also selects N data based on the peak point at which the gesture is completed (N = 20 as in the previous experiment).

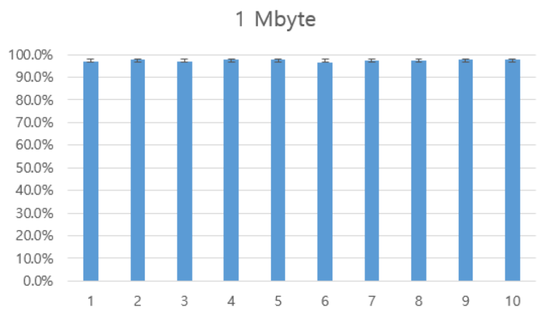

Figure 12 Gesture Recognition Rate and Standard Deviation with Bezier Curve

Figure 12 shows the result of 10 machine learning of a 1 Mbyte gesture dataset in the same manner as the previous experiment. The average recognition rate is 97.36% and the standard deviation is 0.53. It shows significantly higher recognition rate than the previous two experiments and shows a lower standard deviation.

V. CONCLUSION

In this paper, we experimented three methods to obtain high recognition rate when machine learning was done by multi class classification method. First, we found that the recognition rate increases and the standard deviation decreases as the data used for learning increases with the change of recognition rate according to dataset size. Next, we confirmed that we can obtain higher recognition rate by extracting data that can distinguish gesture characteristics from machine learning of section of gesture and machine learning using Bezier Curve.

If more gestures are added, the recognition rate of each gesture is expected to decrease. Rock-scissor-paper Experiments that distinguish three gestures, the first and second experiments have a recognition rate that can not guarantee the scalability of the gesture. When the recognition rate is less than 90%, it is expected that the recognition rate will drop sharply according to the amount of gesture added when the gesture is expanded. On the other hand, in Bezier curve test, the recognition rate was 97% or more with less data. If a sufficient amount of learning data of the added gesture is guaranteed, a recognition rate of 90% or more can be guaranteed even if a lot of gestures are added.

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