Daily Haptic Information Collection System Using ZigBee-based Microcomputer

Shotaro Agatsuma[1], Masafumi Nakagawa[1], Tomoyoshi Ono[1], Shin Takahashi[1], and Satoshi Saga[2]

[1] University of Tsukuba, Tennnodai 1-1-1, Tsukuba city, Japan
[2] University of Kumamoto, Kurokami 2-39-1, Chuo-ku, Kumamoto city, Japan

Abstract. With the progress of machine learning technologies, image-based large-scaled analysis has been taken place. In the field of haptic research, on the other hand, such large-scale analysis has not been reported. This is due to lack of the common framework for collecting haptic information as one of the reasons. Thus, we propose a system to collect acceleration as haptic information by a ZigBee-based microcomputer. We also report an evaluation of the classification ability by the collected information in several machine learning methods to verify the proposed collection method. In this result, our system classifies 8 kinds of haptic information by 93.1% using Convolutional Neural Network (CNN).

Keywords: ZigBee-based microcomputer, daily haptic information, acceleration, machine learning

1 Introduction

With the widespread use of social network services, further many photos and movies have been shared in public by many people explosively. With the progress of machine learning technologies, these massive image-based large-scaled analyses have been done. Especially in the field of computer vision, many sophisticated researchers have been reported. On the other hand, in the field of haptic research, such large-scale analysis has not been reported. This is greatly caused by the fact that common collecting platform of haptic information has not been developed yet [1]. In recent researches, classifying methods of haptic information yield promising results. Though the collection of this haptic information was conducted by each researcher in his/her research and the information often is not open to the public. In addition, most of these researches collected haptic information under limited experimental environments using special device which had many sensors. Therefore, it is difficult to collect haptic information outside of the experiment environment, for example in a daily behavior.

Thus we propose to construct a daily haptic information collection system and to verify the collection method we evaluate the classification ability of the collected information in several machine learning method.

2 Design of daily haptic information collecting system

In this section, we propose a daily haptic information collecting system. Harmon said that haptic information is composed of various data [2]. However, recording all these information simultaneously in daily lives is not realistic. Thus, we focused acceleration in haptic information. It has been recognized as a common framework for haptic information analysis [1]. Therefore, we collect acceleration in our system. Based on the above discussion, we implemented a daily haptic information collecting system. Fig. 1 shows an overview of our system. In the following section, we describe designs of these elements.

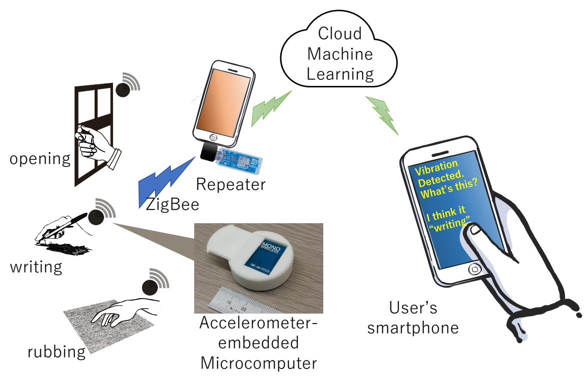

Fig. 1: System overview: the system is consist of ZigBee-based microcomputers (TWE-Lite-2525A [3]), a repeater of ZigBee-Wifi communication (MONOSTICK [4]), cloud server, and client ' s smartphone.

We used the ZigBee-based microcomputer (TWE-Lite-2525A [3]) to collect acceleration. It consist of 3-axis accelerometer and ZigBee wireless module. It can collect 3-axis acceleration with 333 Hz. It is installed on a finger or a pen and collects acceleration as haptic information when them touch objects. The data is relayed to a repeater and sent to a cloud server. The cloud server classifies the data and sends the result to user's device. The server uses machine learning for classificaiton. If the classification result is wrong, the user can input the correct class of the data.

3 Evaluation experiment with the collected data

To evaluate the accuracy of the classification with the collected data through our sensor node, we conducted the following data collection and evaluation experiment of the classification ability. We collected acceleration as haptic information when three participants (3 male, 23 years old) did several activities. These activities are the following 8 patterns. The participants wrote a line with 4 kinds of a pen (pencil, marker, mechanical pencil and ballpoint). The participants also rubbed 4 kinds of texture. These activities are shown in Fig. 2. In each activity, the subjects move his hand in one direction only (from left to right). The moving speed is almost the same (around 50 mm/s). In each activity, 144 sets of data (each set has a length of 5 seconds) are measured. We collected 48 sets of data per person.

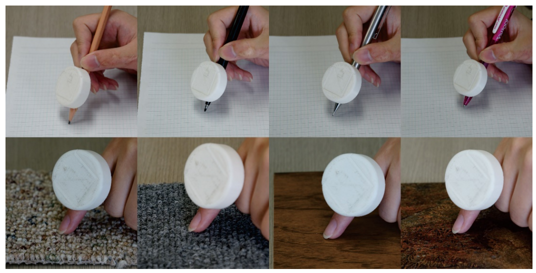

Fig. 2: Activities. top: writing with some pens (from left: pencil, marker, mechanical pencil and ballpoint), bottom: rubbing some textures (from left: thick carpet, thin carpet, wood board and textured tile)

Three machine learning methods, Support Vector Machine (SVM), Multi-Layer Perceptron (MLP) and CNN were used to classify 8 types of data. When using SVM, the acquired acceleration data are processed by Fourier Transform. Our sampling rate of the data is 333 Hz, thus the input vector has 166 dimensions. We employed 70% of all data as training data to parameter tuning. We used MLP which have 1 input layer, 3 intermediate layers, and 1 output layer. In our MLP, a sigmoid function was used between the input layer and the second intermediate layer. Rectified linear unit(ReLU) [5] was used between the third intermediate layer and the output layer. We used the cross-entropy cost function as loss function. We used Adam [6] as weight parameters updating method. Our CNN had 1 input layer, 6 convolution layer, 3 pooling layer, 2 fully-connection layers and 1 output layer. First, the convolution twice on input was performed. Next, the 1×2 max pooling was performed. These operations are repeated three times, and the result is outputted in the fully-connection layer. We used ReLU as activation function in all layers. We also used cross-entropy cost function and Adam. In this experiment, we employed 70% of all data at random as training data and the rest as test data in MLP or CNN.

Table 1: Result of 8 data classification. " ML" stands for "Machine Learning".

ML method	SVM	MLP	CNN
Accuracy (%)	76.0	31.2	93.1

Table. 1 shows the result of classification in this experiment. The accuracy of CNN is greater than the accuracy of MLP or SVM. In this result, We found that it is effective to use CNN to classify haptic data collected our method. These results also show that our proposed system can classify several haptic information.

4 Conclusion

In this paper, we proposed novel collection system of daily haptic information. Nowadays, the collection of the haptic information was conducted by researchers themselves, and the collected information is stored in the laboratory and not open to the public. In addition, the difficulty of labeling ground truth for each data is thought as another reason for the lack of large-scale analysis. Then we proposed a ZigBee-microcomputer based data collecting system which enables large-scale collection and labeling of daily haptic information. Our system consists of ZigBee-microcomputers, a repeater, a cloud server for machine learning and user's labeling application.

With the proposed microcomputer and cloud server, we held two experiments to evaluate the accuracy of classification from the acquired vibrations. We classified 8 types of haptic information. In this result, we obtained 76.0% accuracy with SVM, 31.2% with MLP, 93.1% with CNN. These results show that our proposed system can classify several activity classes with machine learning methods.

In the future, we will collect and classify haptic information from many activities except for the texture rubbing. Also, we will classify more types of haptic information. About this topic, we held an experiment which is a 30 types of classification. At this stage, we achieved about 90% of classification accuracy by using CNN. In addition, we plan to develop a method of making collected data public.

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