A Gesture Recognition System Using a Flexible Epidermal Tactile Sensor Based on Artificial Neural Network

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Abstract—**In this paper, we propose a gesture recognition system using a flexible epidermal tactile sensor by using Artificial Neural Network (ANN). We define five different hand motions and obtain those five hand gestures by using Flexible Epidermal Tactile Sensor. Artificial Neural Network is applied to classify the gestures. The result shows our system has a better performance than the conventional machine learning algorithms like SVM etc. in the recognition rate.**

Keywords-gesture recognition; artificial neural network; hand gesture; flexible epidermal tactile sensor

I. INTRODUCTION

The user interface technology of computing devices has turned a new turning point as smartphones that can be freely used by finger touches have emerged after the personal computer generation where keyboards and mouse were dominant. With the advent of many wearable devices, gesture recognition has once again drawn attention. Users can interact with peripherals with simple body movements using gesture recognition in communication with the devices connected by network. [1] Among them, hand gesture recognition has a great advantage in a variety of human-computer interactions because the devices can be controlled by much simpler motions. There are basically two types of gesture recognition, contact and non-contact gesture recognition. A contact gesture-based interface is a way that a user wears and interacts with a sensor or device in person. Representatively, Both Data Glove [2], [3] using optical fibers, magnetic sensors and gyro sensors and Motion Tracker [4] are examples of contact gesture recognition. The non-contact gesture-based interface is mostly based on visual technology and the process includes initialization, tracking, pose estimation, and recognition. [5] Many existing studies have been studying the shape of hand or hand movements using 2D image data [6]. Although there is an advantage that two-dimensional image data using a single camera is economical, there is a limitation in that robustness due to various environmental changes is limited when using the camera in a real environment. Therefore, existing motion recognition methods are mainly used with pre-arranged gestures in a predetermined place. Since the human body has a very complicated three-dimensional joint structure, there are more cases depending on the recognized angle and shape of the hand. [7] On the contrary, A contact gesture-based user interface is a method in which a user wears a sensor or a device capable of detecting a user's motion to interact with the user. The advantage of the contact method is that it can acquire accurate user gesture information because it uses relatively expensive equipment. Also, since it can utilize three-dimensional information, it is effective especially in interaction with three-dimensional virtual objects.

In this paper, we propose a gesture recognition technology based on Artificial Neural Network using a wearable device with a flexible epidermal tactile sensor touch which has the advantage of the convenience of wearing. The composition of this paper is a s follows. Chapter 2 explains experimental dataset, configuration of experimental system and results of experiment, Chapter 4 explains discussion and conclusion.

II. EXPERIMENT

A. The Dataset

In this paper, the gestures of five different fingers and wrists which are basic state without any movement, bending of the wrist, swelling and spreading of the fingers, are defined as experimental data. The five distinct gestures are shown in Figure 1, Figure 2, Figure 3.

Figure 1. Definition for none state

Figure 2. Definition for bending of the wrest

Figure 3. Swelling and spreading of the fingers

The data were collected from five other participants for experimenters. All the gesture data were collected by attaching Flexible Epidermal Tactile Sensor to the wrist of the experimenters. Flexible Epidermal Tactile Sensor is a s sensor that acquires electrodes on the surface of the skin caused by movement of connected muscles when taking a hand or finger gesture. The logic model of the sensor is shown in Figure 4. [8] The sensor has 16 channels. In this paper, only the signals caught in 10 channels were used for experiment except for overlapping sensors around the wrist. All the experimental data are time series raw data. Roughly 100 data were used as experimental data in each of 5 categories. In all, there are roughly 500 data including 450 training data, 50 testing data.

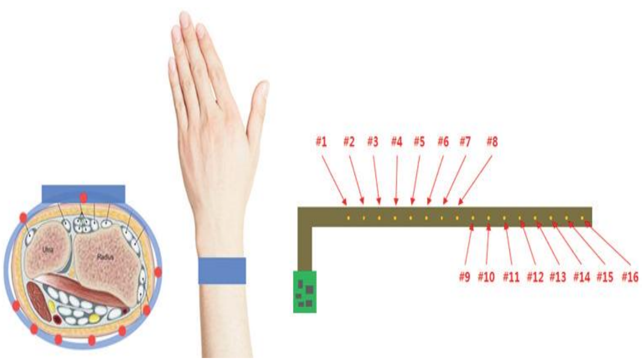

Figure 4. The logic model of the Flexible Epidermal Tactile Sensor

B. Flexible Epidermal Tactile Sensor

The conventional sensors used for gesture recognition are sensors based on MEMS technology.

The non-contact sensor uses a camera, RF / ultrasonic signal, etc. The contact type sensor uses EMG sensor, inertial sensor, FSR sensor, etc.

Sensor-based motion recognition acquires motion information by attaching sensors or markers to each joint of the human body to recognize more accurate human motion. [9] It is a method in which analyzes and uses the data for recognition. Although there is a feeling of discomfort and inconvenience to wear the sensor, Using Flexible Epidermal Tactile Sensor makes users more comfortable and convenient during wearing the sensor.

The electrode signal of the skin surface, which is generated when the muscular palmaris longus are moved, is acquired from the sensor No. 5, and the electrode signal of the skin surface, which is generated when the wrist flexed muscle is moved, is obtained from the sensor No. 6.

As described above, the electrodes on the surface of the skin that are generated when each muscle is moved are acquired from each sensor.

A matching example of the sensor number and the position of the muscle moving reaction is shown in Figure 6. The position of the sensor responding to each muscle is different.

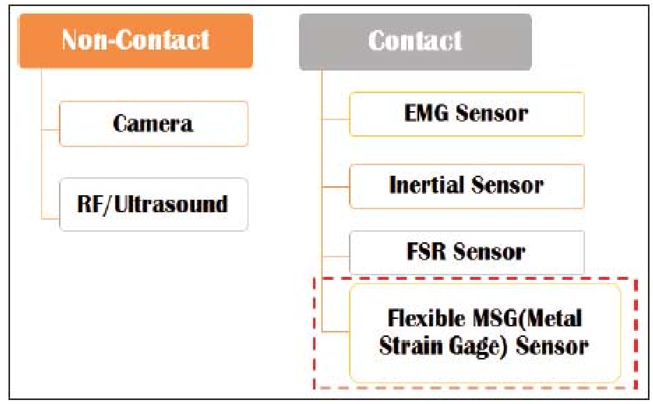

Figure 5. contact and non-contact sensor technologies for gesture recognition

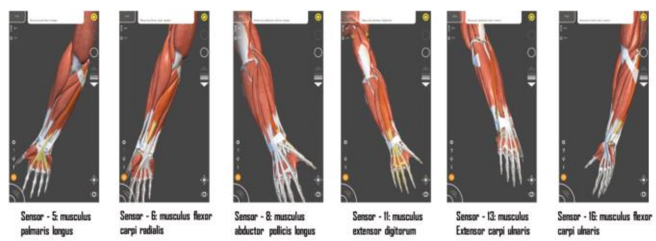

Figure 6. A matching example of the sensor number and the position of the muscle moving reaction

C. Configuration of Experimental System

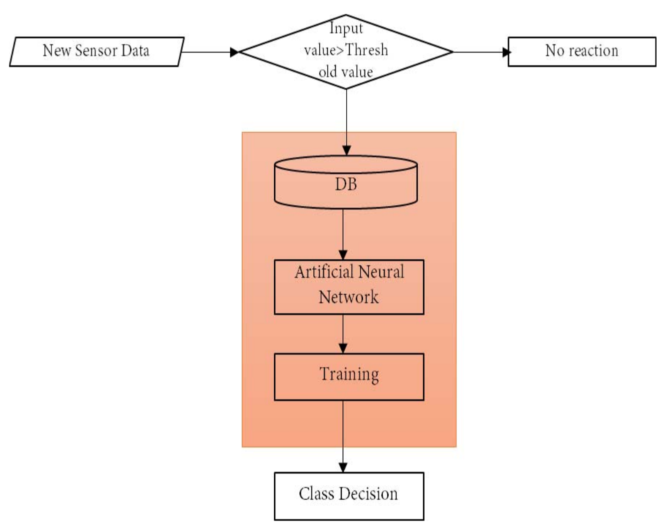

Figure 7. Flow chart of the system

Experiments were carried out by attaching Flexible Epidermal Tactile Sensor to the wrist of the experimenters. And only the channels 4~13 were used by experiment except 1~3 channels and 14~16channels which sensors were overlapped on the wrist. Data is stored by collecting 5 categories of motions separately. a=1 as the activation function and let the learning rate p be 0.01. The flow chart of the experiment is shown in Figure 7. All the collected data constitutes the database through a preprocessing process normalizing the raw data. Training them using the ANN and then the time series testing data would be tested with the input values. In this paper, 10 data are defined as test data for each gesture, and a classification test is conducted for a total of 50 test data sets.

D. *Artificial Neural Network*

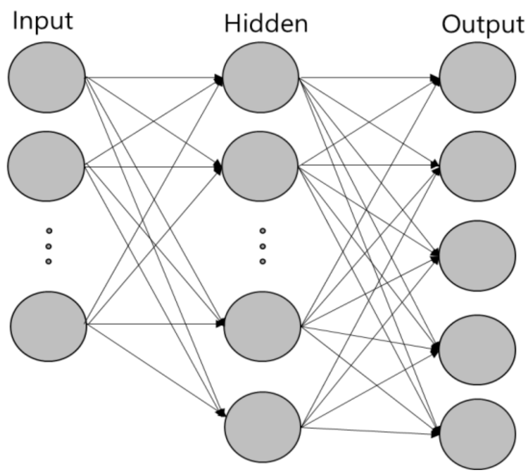

Figure 8. The structure of the Artificial Neural Network

Data obtained from 10 sensors that do not overlap when experimenters worn the sensor on their wrest among the 16 channels is input as ANN input data. An Artificial Neural Network (ANN) was used to classify gestures using surface electrode signals obtained from 10 channels in this paper.

An artificial neural network is a model for calculating a number of output values by assigning weights (connection strength of neural networks) through learning to a large number of input variables. One of the other features of artificial neural networks is that a more sophisticated model can be developed through hidden layers. [10] In the case of existing artificial neural networks, features are extracted and be used as input data. Due to the evolution of training methods, unlike traditional machine learning, it is possible to work with deep layers as a feature extractor by inserting raw data directly without extracting features from direct data.

In this paper, a simple structure is constructed considering the computing environment of a wearable device. The inputs of the input layer contain the normalized values of the raw data from the effective 10-channels data among the 16 channels. The number of nodes in the hidden layer is arbitrarily set.

Finally, the gesture recognition result for the input signal is obtained through the RELU activation function

E. *Result of Experimental System*

In order to compare the performance of the system that classifies the raw data obtained from the proposed Flexible Epidermal Tactile Sensor by ANN in this paper, Support Vector Machine (SVM) algorithm with Integral Absolute Value (IAV) and Difference Absolute Mean Value (DAMV) as input data was used to compare the performance.

The Support Vector Machine (SVM) algorithm is basically is a powerful machine learning algorithm for classification with logistic regression. SVM is an algorithm that extends the concept of perceptron. Perceptron is an algorithm that minimizes classification error, while SVM is an algorithm that maximizes margin. The basic structure of the Support Vector Machine (SVM) is shown in Figure 9.

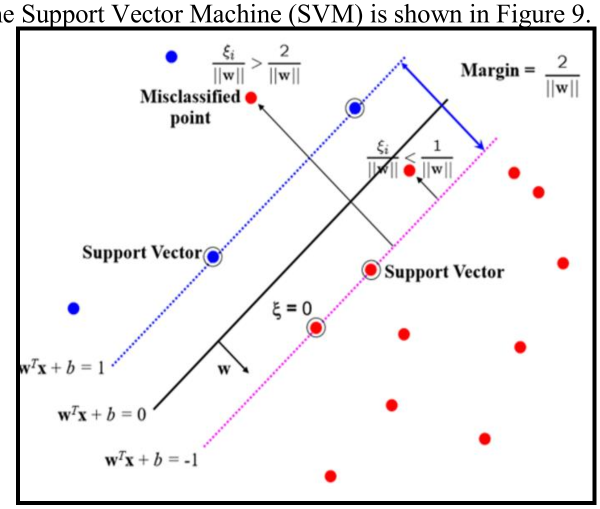

Figure 9. The structure of the Support Vector Machine

The IAV feature vector is an absolute value of a signal over a certain period of time. The equation is as follows (1).

$$\overline{X} = \sum_{i=1}^{N} \left| X(i\Delta t) \right| \tag{1}$$

The DAMV feature vector is a feature that represents the absolute average value of the difference value of each time-series signal and is expressed by Equation (2)

$$\overline{X} = \frac{\sum_{i=1}^{N-1} \left| X(i\Delta t) - X((\mathrm{i}+1)\Delta\,\mathrm{t}) \right|}{N-1} \tag{2}$$

X is the measured signal vector, T is the sampling time interval, and N is the number of samples.

Table I shows the performance comparison between the experimental results of the classifier using ANN proposed in this paper and the results of classifier of IAV feature vector and DAMV feature vector into SVM. The system has an error rate of 0.12% and accuracy of 88%, which is better than 85.47% accuracy using IAV feature vector and 83.33% accuracy using DAMV feature vector in performance comparison.

TABLE I. PERFORMANCE COMPARISON TABLE

	Raw data+ANN	IAV+SVM	DAMV+SVM
Accuracy (error rate)	88% (12%)	85.47% (14.53%)	83.33% (16.67%)

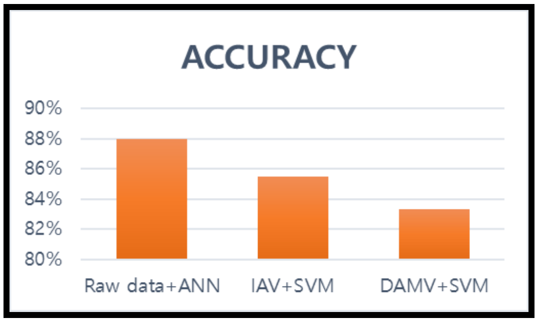

Figure 10. Experimental result

III. DISCUSSION AND CONCLUSION

The user interface technology of the computing device has come to a new turning point with the advent of gesture recognition. Recently, gesture recognition technology has attracted much attention because users can interact with devices by simple body movement through gesture recognition in communication with networked peripheral devices. Among them, hand gesture recognition has a great advantage because it can control the device by simple movements and is not easily affected by the surrounding environment. There are basically two kinds of gesture recognition which are contact and non-contact gesture recognition. A contact gesture-based interface is a way in which a user wears and interacts with a sensor or device in person. There is an inconvenience that the user must wear the sensor, however, since the sensor is attached directly, more accurate operation data can be obtained relatively. Therefore, compared with the non-contact type, gesture recognition research using a wearable sensor capable of recognizing a body posture and movement in any state is actively researched by solving a problem that cannot be recognized by a gesture of a portion where the camera field of view is hidden.

In this paper, A contact-based gesture-based interface were constructed to collect gesture signals, and a wearable device based on a flexible epidermal tactile sensor was used to collect experimental data on the gestures of five different fingers and wrists motions: basic state, wrist bending of the wrist, swelling and spreading of the fingers. The collected data was used as input data of the artificial neural network after simple normalization preprocess. Input the test time series data into the system using ANN, and classify the gesture by the classifier when the threshold is arbitrarily set.

As a result, the classification accuracy of proposed Artificial Neural Network (ANN) is 88%, which is better than 85.47% accuracy using Integral Absolute Value (IAV) feature vector and 83.33% accuracy when using Integral Absolute Value (IAV) and Difference Absolute Mean Value (DAMV) feature vectors together. The result shows our system has a better performance than the conventional machine learning algorithms like SVM etc. in the recognition rate.

Gestures are used when talking to the blind as well as the public. [11] It can be quick and easy for the general person to control information devices by moving a few footsteps or to find and press the remote control. For people with discomfort or disability, being able to control with a simple hand gesture a little away can greatly improve usability and convenience. It is obvious that gestures are a natural action of humans and a good means of expressing their opinions. Thus, Wearable gesture recognition technology research will be continuously tried to recognize and use easier and more natural gestures. [5] Good gestures should be intuitive to use, easy for the user to learn, and extremely easy to remember. [12] For gesture-based devices to be successfully accepted, it is essential to discover the best-suited service and to develop and integrate natural and intuitive gesture technology that suits the service. [5] In the future, it is seemed to be necessary to study gesture recognition data more than daily gesture measurement to provide human proper services.

ACKNOWLEDGMENT

This research was supported by the MSIP (Ministry of Science, ICT and Future Planning), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2017-2015-0-00445) supervised by the IITP (Institute for Information & Communications Technology Promotion).

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