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Wearable Armband for Real Time Hand Gesture Recognition

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***Abstract*—This paper presents a framework for hand gesture recognition based on 3-channel electromyography (EMG) sensors. In the framework, the start and the end points of meaningful gesture segments are detected automatically by checking the cross points of EMG signals and their moving average curves. Then, a classifier combining k-Nearest Neighbor (kNN) and Decision Tree algorithms is used for achieving gesture recognition. For gesture-based control application, a real-time interactive system has been built up for household appliance using 10 kinds of hand gestures as control commands. Our proposed framework facilitates intelligent and natural control in gesture-based interaction.**

Keywords—wearable device; electromyography; gesture recognition.

I. INTRODUCTION

In this paper, we have implemented a wearable armband for real time hand gesture recognition. EMG which measures the electrical potentials generated by muscle cells, can be captured using the non-invasive surface-electrode method, with each pair of electrodes constituting a channel of EMG. Multichannel EMG signals which are measured by EMG sensors placed on the surface skin of a human arm contain rich information about the hand gestures. Many previous researchers investigated various EMG recognition systems which could be controlled by hand gestures, such as prosthetics, robots, and sign language recognition [1]-[3].

The research [1] describes a sign language recognition system which utilizes both a three-axis accelerometer (ACC) and 5-channel EMG sensors. A decision tree and multi-stream hidden Markov models are utilized as decision-level fusion to get the final results. Although its experimental results contain 72 kinds of gestures, the huge mathematical model and the computational complexity make this approach difficult to achieve real-time application. Moreover, the researches [2] presented a prosthesis system implementing the algorithm based on principal components analysis. The experimental results show it can accurately control the prosthetic by 4-channel EMG sensors. However, its recognition process must use computer, which make it difficult to realize on embedded systems.

There are many factors to effect recognition results including hardware circuit design, electrode measurement methods, feature extraction methods and Classification algorithms [3]-[5]. As the armband for real time hand gesture recognition implemented in this paper is a wearable device, all EMG sensors and MCU must be integrated and miniaturized. EMG sensor comprises of instrumentation amplifier, full-wave rectifier, low-pass filter and inverting amplifier. As the total gain of the sensor is very high, significant noise reduction is also achieved. Moreover, there are 4 feature extraction methods: peak value, integral, waveform length and variance. KNN and Decision Tree algorithms are used for gesture recognition.

II. SYSTEM DESIGN

The system architecture is divided into three parts. The first part is the EMG Armband, which is worn on the forearm to measure the user's EMG signal. The EMG Armband transfers the results of gesture recognition to the infrared device to control the household appliances. The second part is the external infrared device. It will receive the results from EMG Armband and identify actions being carried out. The actions may include, for examples, switching TV channels or turning on/off appliances. Moreover, it can learn unknown IR protocol to control additional appliances. The third part is the smartphone App. We developed an Android App for the system. Smart phone devices will play the role of human machine interface. It can set the internal parameters of the infrared device without using computers. These three parts as a whole form a standalone embedded systems.

A. EMG Armband

EMG armband consists of two battery circuits including positive and negative voltage, three EMG sensors and a microprocessor. Modules are connected to each other by DuPont line and fixed on the Velcro strap.

There are two methods to measure the EMG signals. One is the invasive needle-electrode method and the other one is the non-invasive surface-electrode method. The former can measure the electrical signal of a muscle cell. Its advantages include the higher signal noise ratio, high sensitivity and high accuracy for minor muscle shrinks. However, if there are no healthcare professionals to operate, it is easy to get infected and hemorrhage could occur. Thus, in this paper, we used the non-invasive surface-electrode. The surface-electrode patch will measure the electrical signal of muscle cells in the range of the patch and we can find the sum result of surface electromyography signals. Figure 1 shows the electrode which is composed of two tin strips.

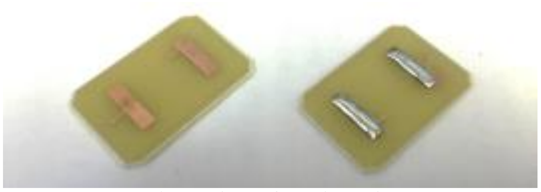

Fig. 1. The surface-electrode.

EMG sensor is used for accomplishing hand gesture recognition. The physiological signals produced by the EMG sensors are measured using the microcontroller unit (MCU) and the feature points are captured for real time gesture analysis. The algorithms of k-Nearest Neighbor and Decision Tree are used for achieving gesture recognition. After the gesture analysis, the result is transferred to external infrared device using Bluetooth.

B. IR Device

Most of the household appliances can use infrared ray (IR) to control so we design an IR device to replace IR remote controller. This study does not need to install additional devices to change the structure of appliances [6]. Moreover, in IR learning system we can learn unknown IR protocol and integrated in our system when users buy new appliances. IR device connects EMG armband and smart device with appliances. It will combines with different networks including Bluetooth and IR, which receive command by Bluetooth and emits IR signals based on command to control appliances.

C. Android Application

Figure 2 shows the screenshot of application interface. There are two functions in this application. One is setting pattern which can decide which appliances to be turned on /off one or more appliances from specified gestures and the other one is remote controlling household appliance.

Fig. 2. The screenshot of application interface.

III. Hand Gesture Recognition

This section describes the analysis and classification of the gesture recognition. Fig. 3 shows the flowchart of recognition system. Recognition system is listed below in sequence from the start to the end: signal capturing, signal preprocessing, active segments, feature extraction and gesture classification.

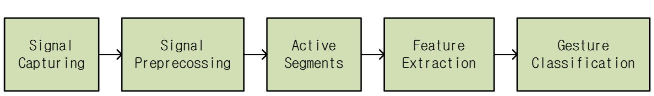

Fig. 3. The flowchart of recognition.

A. Data preprocess

In this paper, we have designed EMG active electrode. It comprises of instrumentation amplifier, full-wave rectifier, low-pass filter and inverting amplifier. Figure 4 shows the flowchart of data preprocess.

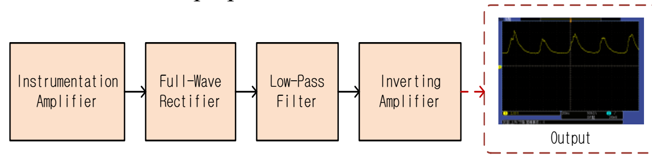

Fig. 4. The flowchart of data preprocess.

B. Feature Extraction

Various kinds of features for the classification of the EMG have been considered in the literature [7], [8]. These features have included a variety of time-domain and frequency-domain. It has been shown that some successful applications can be achieved by time-domain parameters [9]. Feature extraction usually can reflect some characteristics of the original signal. To achieve higher recognition capability, the following four extraction features of the EMG signal are adopted to recognize the complex hand gesture.

1) Peak Value, PV: Calculating the maximum value of the EMG signal at one gesture action,

$$PV = \max(x_1, x_2, \ldots, x_N) \tag{1}$$

where N denotes the data number measured at one gesture action.

2) Integral of EMG, IEMG: Calculating the sum of absolute values of the EMG signal at one action,

$$IEMG = \sum_{k=1}^{N} |x_k| \tag{2}$$

3) Waveform Length, WL: Calculating the sum of the difference values of the EMG signal at one action,

$$WL = \sum_{k=1}^{N} |\Delta x_k| \tag{3}$$

where $\Delta x_k = x_k - x_{k-1}$.

C. k-Nearest Neighbor

The purpose of the k-Nearest Neighbor (kNN) algorithm [10] is to use a database in which the data points are separated into several separate classes to predict the classification of a new sample point. In short, kNN algorithm is that the new data looks for k near points and then new data will be classified by choosing the most point, where k represents a constant.

D. Decision Tree

In our experiments, when this recognition system only use kNN classification algorithm, we get bad recognition rate. As shown in Figure 5, each feature points are so close that recognition result is incorrect.

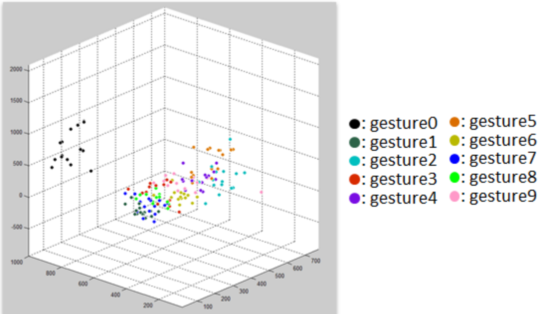

Fig. 5. The sample scatter of peak value.

Even though scale normalization makes the reference values of features to be compatible, it cannot affect the overall classification efficiency. Fortunately, we notice that some features can clearly distinguish the difference among classes and hence reduces the difficulty of classification. To this end, we propose a new classification algorithm namely Decision tree-kNN. As shown in Figure 6, we extract main feature point, which is the integral of EMG, as the first stage of the decision making. Main feature value is an important indicator and can distinguish whether the gesture action is with large energy or small energy. As a result, the original kNN is divided into sub-kNN1 including four gestures and sub-kNN2 including six gestures in Fig.6.

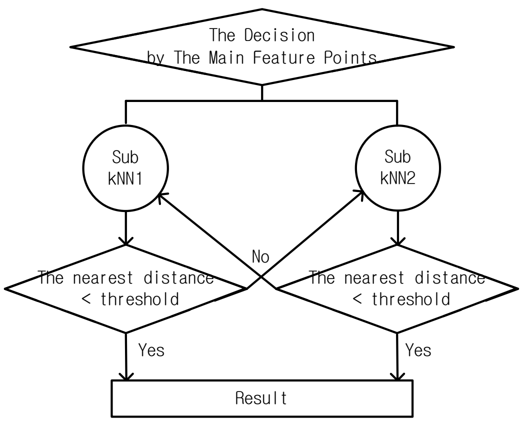

Fig. 6. The flowchart of decision tree-kNN algorithm.

IV. EXPERIMENT RESULTS

We have developed the wearable armband for real-time hand gesture recognition. In the hardware circuit design, this paper has integrated and miniaturized all circuits which are implemented on an armband, as shown in Figure 7. Then, the armband worn on a user hand is shown in Figure 8, where the three EMG sensors are indicated. As to the IR device, its circuit layout and outward appearance are shown in Figure 9 and 10, respectively.

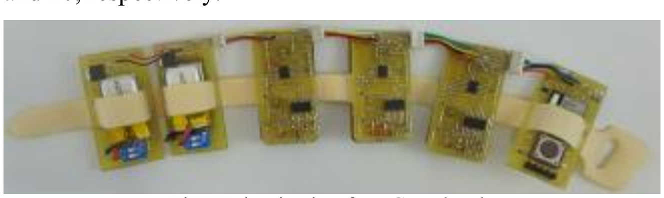

Fig. 7. The circuits of EMG armband.

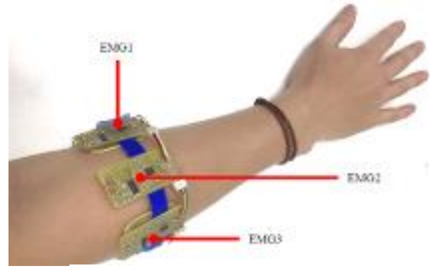

Fig. 8. The Armband worn on a hand.

Fig. 9. The circuits of IR device.

Fig. 10. IR device.

In the software program design, our decision tree-kNN algorithm instantly recognized ten gestures. These ten standard gestures including numbers 0~9 are depicted in Figure 11.

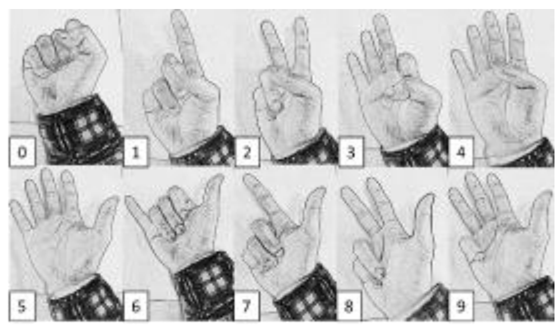

Fig. 11. Gestures used for recognition.

A real application scenario is shown here using a serial of photos. From Figures 12~15, we can see that the user worn the EMG armband, switched TV channels, turn on the lamp, and setting up the pattern using a smart phone, respectively.

Fig. 12. Wearing EMG armband.

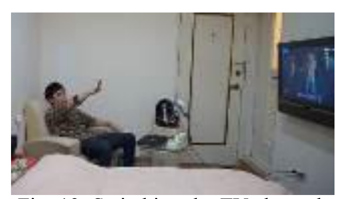

Fig. 13. Switching the TV channels.

Fig. 14. Turning on the lamp.

Fig. 15. Setting up the pattern.

EMG signals are easily affected by external factors including the arm elevation and elbow bending angle. After the experimental measurement, we find that the suitable ranges for arm elevation is approximately $-15^{\circ} \sim +15^{\circ}$ and elbow bending angle is approximately $0^{\circ} \sim +55^{\circ}$, which are shown in Fig. 16 and Fig. 17, respectively. In this range, hand gesture recognition rate is satisfactory.

Fig. 16. Arm elevation range

Fig. 17. Elbow bending angle range

In this gesture recognition experiment, we have recorded the success rate of each gesture. Table I shows that the decision tree classification approach achieved an average recognition accuracy of 69%. Table II shows that the k-NN algorithm approach achieved an average recognition accuracy of 78%. Table III shows an average recognition accuracy of 89% for the tree-kNN algorithm approach. From these results, we can conclude that the new algorithm has improved the overall recognition accuracy.

TABLE I. THE RESULTS OF DECISION TREE CLASSIFICATION.

Gesture	0	1	2	3	4	5	6	7	8	9
Success Rate	$\frac{18}{20}$	$\frac{14}{20}$	$\frac{15}{20}$	$\frac{13}{20}$	$\frac{16}{20}$	$\frac{18}{20}$	$\frac{13}{20}$	$\frac{8}{20}$	$\frac{12}{20}$	$\frac{11}{20}$
Decision tree: recognition accuracy = 69%										

TABLE II. THE RESULTS OF K-NN ALGORITHM.

Gesture	0	1	2	3	4	5	6	7	8	9
Success Rate	$\frac{20}{20}$	$\frac{16}{20}$	$\frac{18}{20}$	$\frac{15}{20}$	$\frac{14}{20}$	$\frac{19}{20}$	$\frac{16}{20}$	$\frac{10}{20}$	$\frac{14}{20}$	$\frac{15}{20}$
k-NN: recognition accuracy = 78%										

TABLE III. THE RESULTS OF TREE-KNN ALGORITHM.

Gesture	0	2	4	5	1	3	6	7	8	9
Success Rate	$\frac{30}{30}$	$\frac{26}{30}$	$\frac{28}{30}$	$\frac{28}{30}$	$\frac{26}{30}$	$\frac{27}{30}$	$\frac{27}{30}$	$\frac{24}{30}$	$\frac{25}{30}$	$\frac{27}{30}$
Sub-kNN1					Sub-kNN2					
tree-kNN: recognition accuracy = 89%										

CONCLUSION

This paper developed a new framework for real time hand gesture recognition which can be utilized in gesture based remote control for household appliance. The presented framework uses multichannel EMG sensors to achieve hand gesture recognition. On the basis of KNN classifiers, the decision tree increases the overall recognition accuracy and significantly reduces the recognition time. This new framework can be used for other gesture based interactions, too. This wearable armband brings people more convenience and gives huge support in life to aged and the injured people.

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