A Proposal for Wearable Controller Device and Finger Gesture Recognition using Surface Electromyography

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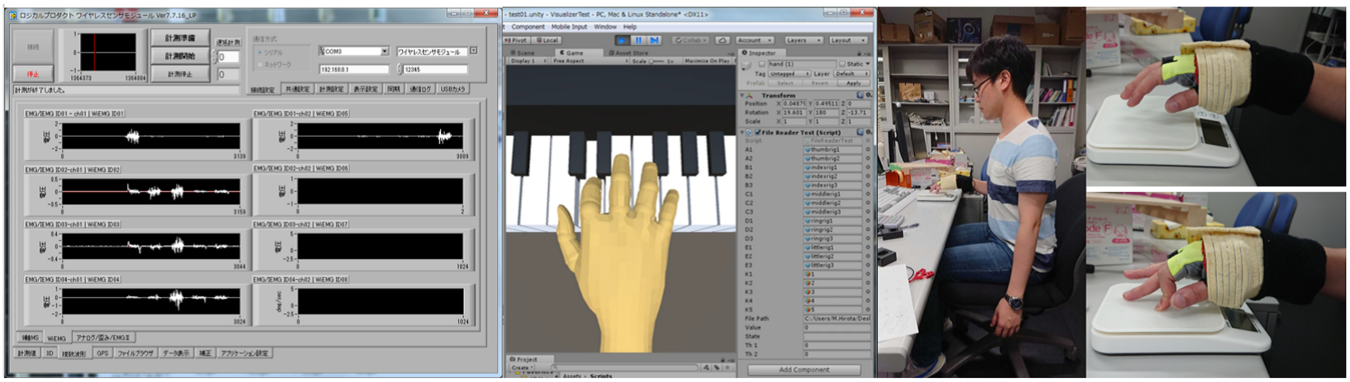

Figure 1: Using wearable finger-less glove controller to identify tapping fingers and realize behavior reflection in virtual space by Unity.

ABSTRACT

Hand and finger motion is very complicated and achieved by intertwining forearm part (extrinsic) and finger part (intrinsic) muscles. We created a wearable finger-less glove controller using dry electrodes of sEMG(surface Electromyography) and only intrinsic hand muscles were sensed. Our wearable interface device is easy to wear and light-weighted. In offline analysis, we identified the tapping motion of fingers using the wearable glove. Totally eleven features were extracted, and linear discriminant analysis (LDA) was used as a classifier. The average of the discrimination result of intersubject analysis was 88.61±3.61%. In online analysis, we created a demo that reflects actual movement in the virtual space by Unity. Our demo showed a prediction of finger motions, and realized the motions in the virtual space.

CCS CONCEPTS

• **Human-centered computing → User interface programming**;

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KEYWORDS

sEMG，Dry Electrode, Finger Gesture Recognition，I/F, Glove Controller

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1 INTRODUCTION

Hand and finger motion is very complicated and achieved by intertwining forearm part (extrinsic) and finger part (intrinsic) muscles. Motion muscle analysis in the forearm is mainly used for power estimation and gesture analysis since myoelectric potential can be collected without directly interfering with hand and finger motion [Chen and Wang 2013; Fang et al. 2014], and delicate finger movement is achieved by the contribution of the intrinsic muscles. A more robust gesture identification is achieved by combining both intrinsic and extrinsic hand muscles [Adewuyi et al. 2016]. In case of performing motion analysis only with the finger part, Robotic gloves are traditionally used to analyze finger-related motion such as Exoskeleton Glove [Ma and Ben-Tzvi 2015]. However, this can cause pain and fatigue on the fingertip and forearm by long-term use due to the weight [Ma et al. 2016]. On the other hand, sEMG

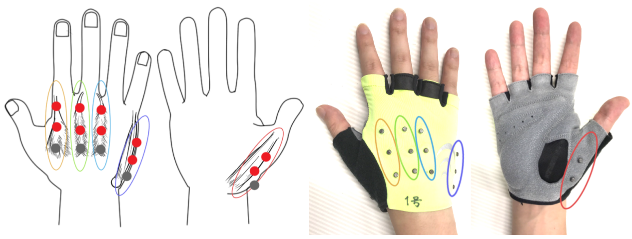

Figure 2: Wearable finger-less glove controller and place of electrodes.

Table 1: The result of recognition.

Tapping Finger	Accuracy(mean±SD) [%]
Thumb	93.79 ± 1.72
Index	85.59 ± 7.56
Middle	72.8 ± 20.22
Ring	75.38 ± 10.12
Little	90.15 ± 10.64
Total Accuracy	88.61 ± 3.62

sensors are light-weighted, and the signals can be used to detect motion quickly. Most of the motion analysis research using sEMG which has been done so far uses paste electrodes [Low et al. 2008], which are not supposed to be used for non-clinical wearable devices. Therefore, we created a wearable finger-less glove controller with dry electrodes, with a demo that identifies motion of fingers from sEMG and reflects the motion in the virtual space using Unity.

2 MATERIALS AND METHODS

The subjects were 11 healthy adult males. And they have never experienced major injuries to the fingers in the past and they have no particular disabilities.

2.1 Procedure

For measurement, a wireless myoelectric sensor (Oisaka electronics) was used. Our glove-type controller and positions of electrodes and the muscles are shown in Fig.2. We analyzed tapping motions of fingers as a popular finger-oriented gesture. We set the most comfortable state as the neutral position. The tapping action of each finger was performed with power of 80%MVC (maximum voluntary contraction). Each state was continued for 2 seconds, and the tapping action of each finger was performed during the Neutral state(Neutral
→Thumb→Neutral→Index...→Neutral). Totally 15 sets were measured for one subject and 22 seconds as one set. The sampling frequency was set to 100 $[Hz]$.

2.2 Analysis

Acquired sEMG signals were passed through a notch filter and butterworth filter by Matlab to remove noise. The temporal window size was set to 20 samples and shifted by 1 sample. Totally eleven features similar to [Adewuyi et al. 2016], IEMG, sign change frequency, zero crossing, waveform length, standard deviation, sixth order Autoregressive coefficient were extracted, and linear discriminant analysis (LDA) was used as a classifier.

3 RESULT AND DISCUSSION

Totally 363,000 samples were collected in our experiment. Table1 shows the result. The accuracy was 88.61±3.62%. Our result showed the discrimination rate of the middle and ring finger was found to be lower than the other fingers. The result may indicate that the motion of the middle and ring fingers has less dependency to the intrinsic muscles targeted this experiment than other fingers. Fig.1 shows how the actual operation is reflected in the virtual space by Unity as demonstration.

4 CONCLUSION AND FUTURE WORK

In this study, we created a wearable finger-less glove controller using dry electrodes.The glove can be used to detect tapping motions of each finger. Even when we used dry electrodes and the data of the same subject was not existed in the train data, an average accuracy of 88.61% was recorded. We also showed an application to demonstrate the finger-motion identification in the virtual space. In the future, we would like to realize more variation of finger-related motions.

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