2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI)
August 19~22, 2016 at Sofitel Xian on Renmin Square, Xian, China

Development of a Wearable HCI Controller through sEMG & IMU Sensor Fusion

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***Abstract*—This paper studies a novel wearable human-computer interface that allows a user to interact with computer-based applications through the fusion of sEMG and IMU sensors. The proposed system is able to detect human motion intention, specifically, the gestures of the wrist and hand. It then translates the gestures and transmits it as command signals for computer-based applications. The novelty of the proposed system is the training-free control scheme to decode sEMG signals into target motions. The classified gestures could be identified by two sEMG sensors mounted on a forearm. One IMU sensor is used to calculate the real-time arm configuration. This can be a command signal for a cursor position in a computer-based application through the proposed projection method. Our method also comprises the drift compensation algorithm which makes our system more robust in prolonged operation. It also makes a user feel more comfortable. For evaluating the applicability of the proposed method, we developed a presentation controller that allows the user to control the mouse cursor, and three distinctive commands using wrist and hand gestures. The proposed system is validated by experiments with six subjects.**

***Keywords*—Human-Computer Interface, sEMG, IMU, non-training classification.**

1. Introduction

Human-computer interface (HCI), has been widely studied to understand the interaction between human and computer and to achieve intuitiveness and robustness. Bionic interfaces have been recently studied as HCIs, because they directly and intuitively measure the human motion intention. For example, Electrooculogram (EOG) [1] and Electro-Encephalogram (EEG) [2] can be applied to both normal and disabled person. In particular, bio-signals such as Eletromyogram (EMG) [3-6] are commonly used as input signal for HCI applications because they can be detected prior to actual human movements. A sEMG based interface for wheelchair users with severe motor disabilities was presented using the double threshold method, to discriminate a time difference of muscle activation [7]. In addition, hand gesture recognition system for virtual game control was developed using two-stream HMMs, from a 3D accelerometer and multi-channel EMG sensors [8]. A novel mouse controller based on the sEMG and IMU signal was also introduced. The sEMG signal was recognized by employing LDA method to classify five hand motions. The cursor movement was achieved by the integration of accelerations [9]. Furthermore, mobile technologies are rapidly increasing the number of wearable-sensor devices. Therefore, wearable

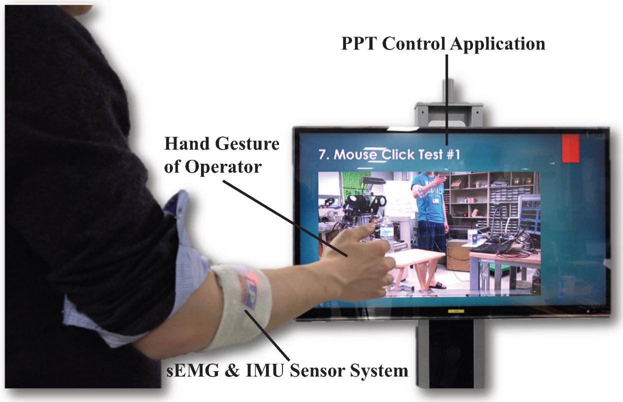

Fig. 1. HCI controller using sEMG & IMU sensor: The propose HCI controller can control the presentation slide using hand gestures.

bionic interfaces are being widely studied in HCI applications.

However, current sEMG and IMU sensor based HCI methods have some limitations. First, for proplonged operation, sEMG signals are time-varying because of muscle fatigue. Second, a training process is required before utilizing sEMG signals to obtain learning parameters. Given that these parameters are usually assumed to be time-invariant, it will lower the classification accuracy. Moreover, the tendency of sEMG signals vary depending on different operators. This is true even in case of same motion configurations. Moreover, a cursor movement using accelerations or angular velocity in the previous studies could not provide intuitiveness to the operator.

In this study, we proposed a HCI controller using sEMG and IMU sensors to transfer human gestures to a computer-application, i.e., a presentation controller. Fig. 2 shows the framework of the entire system.

The proposed method does not need training process for mapping the sEMG signals to gestures prior to classification. The cursor movement control is achieved by using one IMU sensor attached on the forearm and a mapping algorithm from the configuration of a forearm to a screen. This paper is structured in the following sequence: Section 2 describes how to implement the proposed system using sEMG and IMU sensors. In section 3, the proposed algorithm for motion

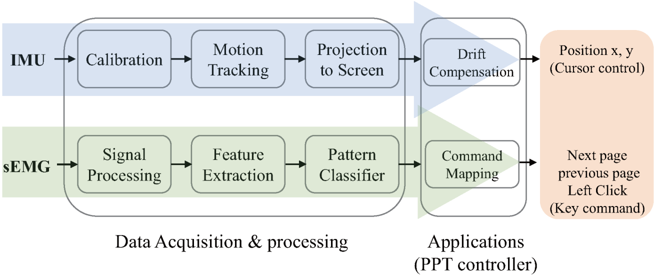

Fig. 2. Framework of entire system: The proposed system consists of two main data streams, which are IMU data and sEMG data.

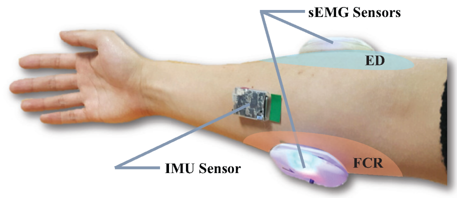

Fig. 3. The location of attached sensors and correlated target muscles (FCR, ED)

classification, cursor control mapping, and drift compensation is introduced. Section 4 shows experimental results of demonstration and classification accuracy. It is followed by discussion, conclusion, and future works in section 5.

2. System Description

A schematic diagram of the proposed system is described as shown in Fig. 2. There exist two main data streams: IMU data flow and sEMG data flow. All the programs exploited in this study were implemented using C++ language. All data measured by the sensors are gathered with signal processing, and then, the proposed controller generates proper commands using the data sets. The proposed controller and presentation application are communicated via TCP/IP protocol. In this section, the whole system for the proposed HCI controller is described in detail.

2.1. Experimental Setup

sEMG signals were recorded through a dry-type sEMG data acquisition system(Shinystone, LogOnU Inc.). This sensor provides a sampling frequency of 1 kHz with 2.4 GHz wireless communication protocols. We combined Inertia Measurement Unit (IMU) sensor (EBIMU24GV2, E2BOX Co.) in order to measure the joint configuration of a user's forearm. The sampling rate of IMU sensor is 100 Hz, which is ten times smaller than that of sEMG sensor; however, it is sufficient for the capture of human motion in our application. The proposed system is advantageous to wear, because the sensor is wireless and band-type. The band-type sensor can enhance the wearability, which is one of the important requirements of bionic interface for HCI. In this research, we validated the developed HCI controller by implementing it in experiments with six healthy subjects aged 27-30.

2.2. Hand Posture Detection using sEMG Sensor

Raw sEMG signals were transmitted to computer via USB 2.0 protocol. They passed through the Band-Pass filter (20-500 Hz) and notch filter (59-61 Hz) for noise cancellation in consecutive order. Then, the sEMG signal is fully rectified and filtered using a moving average filter having a sample data window size of 100[10][11]. From a pilot experiment, we found two muscles that are dominant in the classification of three target hand postures (wrist flexion, wrist extension, and clenching). We placed our sensors on these two muscles (Flexor Carpi Radialis (FCR) and Extensor Digitorum (ED)) as shown in Fig. 3. the details of the motion detection algorithm using sEMG signal will be presented in section 3.1.

2.3. Arm Motion Tracking using IMU Sensor

To capture arm motion of the operator, a IMU sensor was attached to the forearm. With a calibration method [12] that calculates the relative transformation between sensors and human body segment, precise attachment location or rotation of sensor is unnecessary due to calibration method. IMU sensor communicates via wireless radio frequency to obtain rotation information in the form of Euler angles or Quaternions. From this output of sensor, we can estimate human joint configuration with a predefined kinematic arm model. Through forward kinematics, we can estimate the wrist position. To acquire cursor movement from sensor, an additional mapping algorithm is applied (see section 3.2) to obtain the desired two-dimensional cursor position in the screen from three-dimensional forearm configuration.

2.4. Presentation Control Application

Presentation control application is composed with a drift compensation algorithm and a mapping algorithm. They determine the a relationship between a user's gestures and commands for presentation control. In this study, we create mapping pairs as (wrist flexion - previous slide), (wrist extension - next slide), and (clenching - left click). This mapping can be changed according to user preference at operator's discretion. In addition, we applied a voting concept to avoid execution of all commands that we're delivered erroneously from a previous step.

3. Proposed Methods

3.1. Motion Classification using sEMG Signal

The proposed pattern classifier does not need additional learning algorithms or training data. In other words, we do not use a supervised learning scheme. Which is a significant advantage of our approach, because it reduces the initialization time of our system compared to other sEMG-based supervised classification methods. On the other hand, the proposed classifier utilizes an intuitive prior information

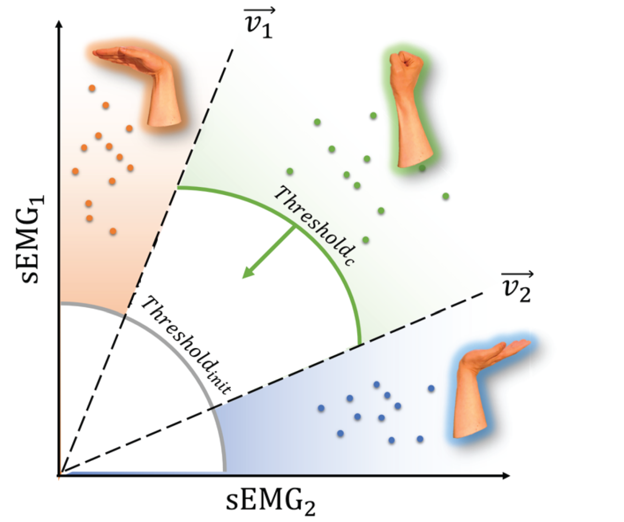

Fig. 4. Classification concept diagram with two sEMG sensors for three target motions: Wrist flexion, wrist extension and clenching. Reference vectors ($\vec{v}_1$, $\vec{v}_1$) are determined by a separation gain V. δ_i is a initial threshold and δ_c is classification threshold which varies over time.

about sensor positions attached to human skin. Our method builds a vector-based model according to a prior knowledge of feature pattern of target motions. The proposed method is feasible because there are only three target motions in the HCI system. Traditional data-based learning schemes have struggled with time-varying characteristic of sEMG signals, which shows different pattern from learned model (training data) with respect to time. Thus, our proposed classifier can flexibly adapt to time-varying characteristics of sEMG signals whereas the model-based classifier can not handle it.

In this study, we used wrist flexion and extension gestures for presentation commands because it is intuitive to map between gestures and presentation control commands, i.e., page forward and backward. From a pilot study, we additionally found that sEMG pattern of clenching (power grasp) motion is well distinguished with that of wrist flexion and extension. This result is derived from the power grasp posture, which utilizes both FCR and ED while wrist flexion and extension have a dominant muscle.

Prior to classifying the signal, filtered sEMG signal can be represented with two dimension vector as (1):

$$\mathbf{e}(k) = [e_1(k), e_2(k)]^T \in \Re^{2\times 1} \tag{1}$$

where k denotes the sample index of signal, $e_1(k)$ and $e_1(k)$ are sensor value from sensor channel 1 and channel 2 respectively. The norm of signal can be calculated as (2):

$$\|\mathbf{e}(k)\| = \sqrt{e_1^2(k) + e_2^2(k)} \tag{2}$$

.

With this information of $\mathbf{e}(k)$ and $\|\mathbf{e}(k)\|$, our proposed pattern classifier determine most-likely class ($C(k)$) through following conditions:

$$C(k) = \begin{cases} 0 & \|\mathbf{e}(k)\| < \delta_i \\ 1 & e_1(k) > V * e_2(k) \\ 2 & e_2(k) > V * e_1(k) \\ 3 & (\frac{1}{V}e_1(k) < e_2(k)) < Ve_1(k))\,\&\,(\|\mathbf{e}(k)\| > \delta_c) \end{cases} \tag{3}$$

where V is a separation gain to determine reference vectors. δ_i and δ_c are pre-defined thresholds for initial condition and classification for clenching motion, respectively. In this study, the value of V was set to 4; this value controls the size of each motion region (red, green, and blue) in Fig.4. The output value 0 implies rest, 1 implies wrist flexion, 2 implies wrist extension, and 3 indicates power grasp motion. This classification strategy in feature vector space is well described in Fig. 4.

3.2. Cursor Control

In previous work, we succeeded in tracking the joint value from human arm in real-time [12]. This was achieved using several IMU sensors; the sensors were attached to human body link, between each joints. We successfully tracked human arm motion including shoulder, elbow, and wrist joints. In this study, the problem is simplified by eliminating the number of sensors, which is an improvement over the previous study. Only one sensor is attached to the forearm muscle to track human arm motion with the assumption that the human arm is considered as one link. With Rotation information of the sensor (R_s), the position of body kinematic model can be obtained through forward kinematics. Then, the relative 3D position (P_r) of human arm and shoulder from the kinematic model can be calculated as below:

$$P_r = P_{\text{arm}} - P_{\text{shoulder}} \tag{4}$$

where P_{arm} and P_{shoulder} are defined in global frame in 3D space. To control the cursor movement, it is unnecessary to use x-coordinate of global frame represented as Fig. 5. Therefore, we only exploit y and z coordinates of P_r through projection along x-axis of global frame. Consequently, the desired position of x and y coordinate (represented with upper index) in the screen is described as:

$$P_d^x = s \times P_r^y + C_{init}^x \tag{5}$$
$$P_d^y = s \times P_r^z + C_{init}^y \tag{6}$$

where s is a sensitivity gain, which determines the degree of human movement that will be delivered to screen cursor. C_{init}^x and C_{init}^y are the initial calibration offset term for x and y coordinates, respectively. These initial calibration offset were set to half the resolution of the width (W) and height (H) of monitor which can be automatically obtained from the windows operating system. A sensitivity gain, or s, can be regarded as a scaling factor that determines the size of the user plane, which will be applied to deliver motion. For example, if s is large, the size of the user plane is small. This leads to the conclusion that a small movement by a human can bring about

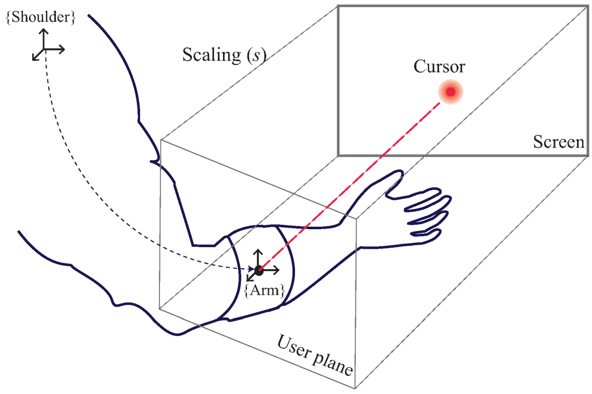

Fig. 5. The conceptual figure of projection method using IMU sensor to control cursor position in the screen.

a large movement of the cursor. While s is relatively small, operator requires a large motion to transfer a same amount of cursor movement.

3.3. Moving User Plane - Drift Compensation

The other advantage of proposed control method is the capability to move the user plane. If human operator can move their user plane, they can flexibly change the reference of user plane based on their comfort of using the proposed system. On the other hand, our main drawbacks of using the low cost MEMS-based IMU sensor is a drift problem, in which errors are accumulated and lead to large errors over time [13]. Thus, it is natural that the drift problem can result in low robustness of our cursor control system. If errors are accumulated, the relationship between desired position on the screen and current position will be in discordance. Moving the user plane can compensate for this drift problem. This can be done by changing the calibration offset gains with an error calculated from the desired position and current position of the cursor. If desired position is outside the user plane, the error becomes larger than zero. Since we use the sensor signal with a discrete time with sampling frequency, the algorithm for updating the calibration offset gain at kth sample is explained as below:

$$P_d(k) = s \times P_r(k) + C(k) \quad (7)$$
$$P_c(k) = Getcursorposition(k) \quad (8)$$
$$C(k) = C(k-1) + e(k) \quad (9)$$
$$e(k) = \begin{cases} 0 & \text{if } P_d(k) \in S \\ P_d(k) - P_c(k) & \text{if } P_d(k) \notin S \end{cases} \quad (10)$$

where P_c is a current cursor position and S denotes the screen plane. If the desired position of the cursor exceed limits of screen, the error becomes non-zero and this error value is updated to the calibration offset. With this algorithm, we can handle the moving user plane with human intention and also resolve the drift problem of IMU sensors. Detail pseudocode is described in Algorithm.1.

Algorithm 1 Moving User plane algorithm

```
function MOVING USER PLANE (R_s)
    P_r = CALCULATE P_r (R_s)                      ▷ Equation (4)
    P_d = CALCULATE P_d (P_r^x, P_r^y)             ▷ Equation (7)
    P_c = GETCURRENTCURSORPOSITION()
                                    ▷ Winow library funtion
    e = GETERROR(P_d, P_c)                         ▷ Equation (10)
    UPDATE CALIBRATION OFFSET(e)                   ▷ Equation (9)
end function
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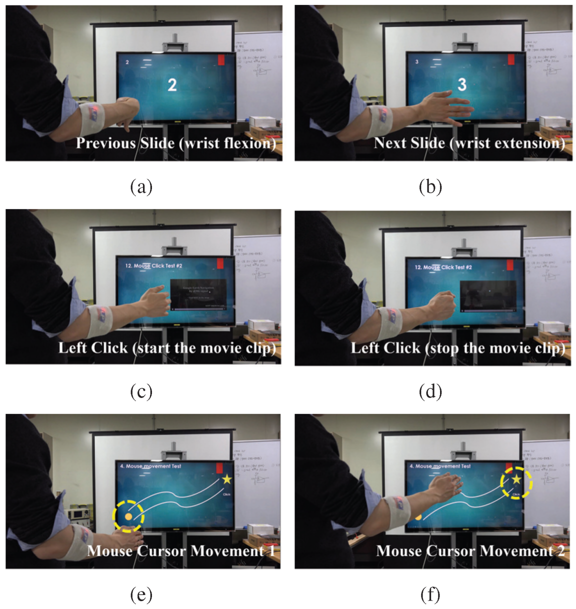

Fig. 6. Demonstrations of HCI controller. (a) previous slide(wrist flexion), (b) next slide(wrist extension), (c) left click to start the movie clip(clenching), (d) left click to stop the movie clip(clenching), (e) mouse cursor movement (bottom left), (f) mouse cursor movement (top right).

4. Experiment Result and Demonstration

Fig.6 shows the demonstration of the proposed HCI controller. HCI controller in real-time can successfully control presentations to generate three commands(previous slide, next slide and left click) and move the mouse position. Using a fundamental vector based classifier, the classification success rates are calculated in tougher conditions for the improving the accuracy of every sampled data in the entire sampling period. Threshold for the majority of vote schemes (vote size was set to 30) were also applied in this simulation. The classification accuracy results are shown in Fig. 7.

Six subjects participated in order to validate the superiority of our proposed system. Experimental results show that the average accuracy of the proposed sEMG classification is above 85%. This degree of accuracy makes our proposed system more robust and user-friendly. Based on the users' experience, the non-training algorithm was shown to be effective in handling the time-varying characteristics of sEMG signals.

The experimental results show the endurance of our non-training method. In addition, as time passes, the accuracy of

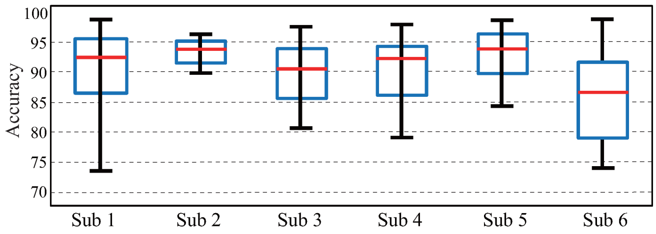

Fig. 7. Classification accuracy for all subjects

our classification method is maintained at similar levels as that during initial conditions. This indicates the advantage of utilizing the non-training method.

5. Conclusion and Future Works

In this study, we proposed a novel HCI controller combined with sEMG and IMU sensors. The proposed system controls the mouse cursor movement and generates key input for the presentation controller, by human gesture detection. The sEMG signals of two pre-determined muscles (FCR and ED) are exploited to classify three distinctive target hand gestures: wrist flexion, wrist extension, and clenching. One IMU sensor which is attached to the operator's forearm was utilized for the control of the mouse cursor position. The kinematic model of the human arm with the proposed calibration method is used to estimate the human hand position. This is converted to cursor position in the screen by the projection method and the drift compensation algorithm. In particular, the drift compensation algorithm makes our system more robust in long term usage. It also makes the proposed system more user-friendly by moving the user plane. As a result, the proposed HCI controller with human motion has the capability of cursor control and gesture recognition. For future work, we plan to combine the IMU sensor and sEMG sensor in one sensor module to make the system simple and easy to use. In addition, we solve the problem of our current framework, such as acquiring sEMG signal from pre-defined target muscles, which is hardly to achieved by an unskilled operator. For this reason, we plan to expand the sensor system to an eight-channel system with an arm-band type. This will enable us to acquire as much information as possible from muscles and increase the number of target motions, while keeping the training-free control scheme with high accuracy of classification.

Acknowledgement

This work was supported by the Global Frontier R&D Program on [Human-centered Interaction for Coexistence] funded by the National Research Foundation of Korea grant funded by the Korean Government(MSIP) (NRF-M1AXA003-2010-0029748) and the convergence technology development program for bionic arm through the National Research Foundation of Korea(NRF) funded by the Ministry of Science, ICT & Future Plannig (No. 2014M3C1B2048419).

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