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A Real-time EMG-based Assistive Computer Interface for the Upper Limb Disabled

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Abstract—**This paper presents the design of an assistive real-time system for the upper limb disabled to access a computer via residual muscle activities without standard computer interfaces (e.g. a mouse and a keyboard). For this purpose, electromyogram (EMG) signals from muscles in the lower arm were extracted and filtered using signal statistics (mean and variance). In order to control movement and clicking of a cursor from the obtained signals, six patterns were classified, applying a supervised multi-layer neural network trained by a backpropagation algorithm. In addition, an on-screen keyboard was developed, making it possible to enter Roman and Korean letters on the computer. Using this computer interface, the user can browse the Internet and read/send e-mail. The developed computer interface provides an alternative means for individuals with motor disabilities to access computers. A possible extension of our interface methodology can be incorporated in controlling bionic robot systems for the limb disabled (e.g. exoskeletons, limb prostheses).**

I. Introduction

To date, many researchers have developed alternative interfaces to allow the upper limb disabled to access computers. Recently, neural signals have been attracting attention with respect to extracting user's intention, as these signals provide information related to body motion faster than other means (e.g. kinematic and dynamic interfaces). Notably, a variety of methods have been developed to execute a user's intention: from brain or muscle activities.

At the central nervous system (CNS) level, signals from brain activities are applicable candidates to extract human thoughts. The electroencephalogram (EEG) [1] is a non-invasive monitoring method to record brain activities on the scalp. However, the signals acquired via this method are massed activities of many cortical neurons, and provide low spatial resolution and a low signal to noise ratio (SNR). On the other hand, invasive monitoring methods capture the activities of individual cortical neurons in the brain [2]. However, many fundamental neurobiological questions and technical difficulties need to be solved [3], and interface methods based on brain activities generally require extensive training [4]. Despite these challenges, research in this area shows promise for helping people with severe motor disabilities (such as loss of skeletal muscle control from below the shoulders).

A standard signal in a peripheral nervous system (PNS) level is the electromyogram, (EMG) [5] which represents muscle activations. EMG signals can be measured more conveniently and safely than neural signals at a CNS level. Furthermore, this non-invasive monitoring method provides good SNR. Hence, EMG-based HCI implementation is more practical with current technology.

This paper presents an EMG-based computer interface that enables the upper limb disabled, such as quadriplegic (C7, C8 functional level) patients and hand amputees, to access a computer without standard computer interfacing devices (e.g. a mouse and a keyboard), as depicted in Fig. 1. Using the developed computer interface, users can alternatively control movement of cursor and click buttons through muscle activation in the lower arm. Also, using the designed on-screen keyboard, they can enter Roman and Korean letters on the computer. In order to confirm the utility of the developed computer interface, an experimental study was conducted to evaluate performance by applying Fitts' law, which is a model that quantitatively evaluates the effectiveness of a computer pointing device. While some researchers have presented similar computer interfaces from EMG signals [6, 7], they have focused mainly on implementation of the interface and have not quantitatively

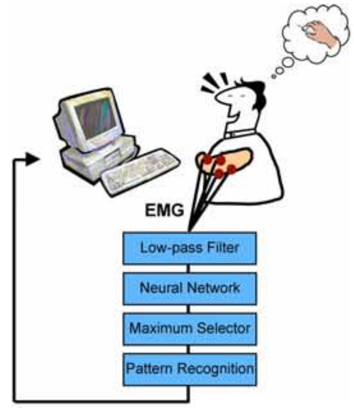

Fig. 1. Conceptual diagram of the developed EMG-based computer interface

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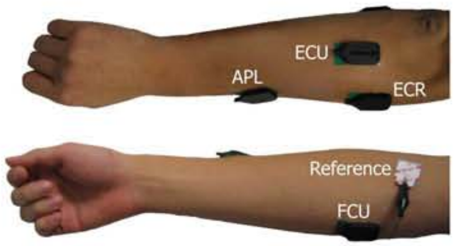

Fig. 2. Myoelectric sites for extraction of EMG signals

evaluated the performance of their computer interfaces.

II. Methods

A. Myoelectric Site Selection

Usability via alternative access to a computer is dependent on how well the user can control the computer in a natural and intuitive manner. For this criterion, four different wrist movements (e.g. radial deviation, ulnar deviation, wrist extension, and wrist flexion), which can be mapped to cursor movement commands (e.g. left, right, up, down), were chosen to express the user's intention. Based on these movements, the user can control the cursor intuitively, because the direction of wrist movement corresponds with that of the cursor movement. For mouse button clicking and stop commands, the motion of finger extension and resting were selected, respectively.

There are approximately 20 muscles on the lower arm, which together make a large contribution toward moving the wrist or a finger [8]. The required motions for the interface were not all wrist motions (e.g. supination or pronation) but rather just six motions. Thus, when each muscle contraction was held, four muscles were selected from the total muscles by palpation: the flexor carpi ulnaris (FCU), extensor carpi radialis (ECR), extensor carpi ulnaris (ECU), and abductor pollicis longus (APL). Since quadriplegic patients (C7, C8 functional level) can still weakly activate these muscles [9], the selection of the muscles as myoelectric commands is plausible. Fig. 2 shows the locations of electrodes on the skin of the lower arm to observe EMG signals.

B. Data Collection and Signal Processing

Four active surface electrodes (DE-2.1, Delsys) and a data acquisition board (PCI 6034e, National Instrument^{TM}) were used to collect EMG signals. Each signal is sampled at 1 kHz and amplified 1000 times. It has been well established that the EMG signal can be modeled as a zero mean Gaussian process [10, 11]. On the basis of this knowledge, the variance of the signal can be easily estimated for feature extraction and low-pass filtering, as follows:

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{N}\left(M_i - \overline{M}\right)^2}{N-1} \tag{1}$$

where M_i is the magnitude of the ith signal, N is the number of data in a window, and $\overline{M}$ is the mean of magnitude of N signal data, respectively. The function form of variance is analogous to a moving average filter except for a square term and a denominator. A squaring process increases the degree of the difference between the activation state and inactivation state of the muscle. Therefore, the use of variance to extract the EMG feature is more effective than using only a moving average.

Since the function of variance is similar to the function of a moving average filter, the cut-off frequency of the low-pass filtering employed here can be defined corresponding to that of a moving average filter, as follows:

$$f_c = \frac{f_s}{2N} \tag{2}$$

where f_s is the sampling frequency. If a large number of data are used, the effectiveness of the low-pass filtering will be increased substantially. However, this introduces a time delay in estimation of the user's intention. Hence, there is a tradeoff between the effectiveness of low-pass filtering and real-time signal processing. Currently, there is no standard related to the issue of perceivable delay, but Englehart *et al.* [12], Ajiboye *et al.* [13], and Soares *et al.* [14] have defined the perceivable delay as 300 ms, 100 ms, and 100 ms, respectively. In our work, we defined the number of data in a window for low-pass filtering as 100. In this regard, the process not only provides effective low-pass filtering (f_c = 5 Hz), but also does not introduce a significant time-delay.

C. Pattern Recognition

A supervised multi-layer neural network was used to recognize the user's intention. The structure of the neural network is as follows:

- hidden layers: 2
- hidden neurons: 10
- input neurons: 4
- output neurons: 6

For neural network training, a backpropagation algorithm was used, and the training parameters were:

- learning rate: 1.2
- momentum: 0.8

Table I shows the target vectors to discriminate classes of movement from the EMG signals. In addition, a maximum

TABLE I
Target vectors to classify user's intention

Class of movement	Desired network's response					
Stop	1	0	0	0	0	0
Left	0	1	0	0	0	0
Right	0	0	1	0	0	0
Up	0	0	0	1	0	0
Down	0	0	0	0	1	0
Click	0	0	0	0	0	1

Fig. 3. The developed on-screen keyboard

selector was located at the end of the network in order to select the most activated neuron at the output layer. Therefore, the user's intention can be identified by matching the most activated neuron to a class of movement.

D. On-screen keyboard

Fig. 3 depicts the developed on-screen keyboard to help the upper limb disabled enter Roman and Korean letters on a computer. The size of this interface is 6.2 cm × 10.6 cm, and each button is a 1.5 cm × 1.2 cm rectangle situated on the interface. There are 15 buttons on the interface representing the letters 'a' to 'z', 'SPACE' (→), 'ERASE' (←), etc. This interface is inspired by the interface system of the Samsung mobile phone [15]. Movement of the cursor is restricted discretely only on each button in order that the user can easily use the interface.

D. Performance Evaluation

For the performance evaluation, a Fitts' law test [16] was designed. Fitts' law is a model to quantitatively evaluate the effectiveness of a computer pointing device (see review [17]). This experiment was divided into two sessions: use of the developed computer interface and use of a mouse. For this study, five subjects (S1-S5) with intact limbs volunteered and a paired experiment was run. (A detailed description of the performance evaluation for our computer interface can be found in [18]). In this test, the efficiency of the computer pointing device is defined by the index of performance (IP), which represents how quickly pointing and clicking can be done using the computer pointing device. A high IP value illustrates that a large quantity of information (bits) can be transferred per second.

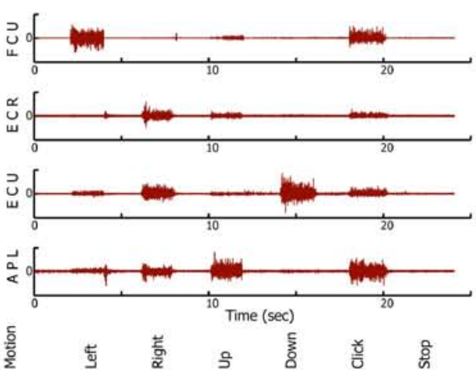

Fig. 4. EMG signals from four muscles (FCU, ECR, ECU, and APL)

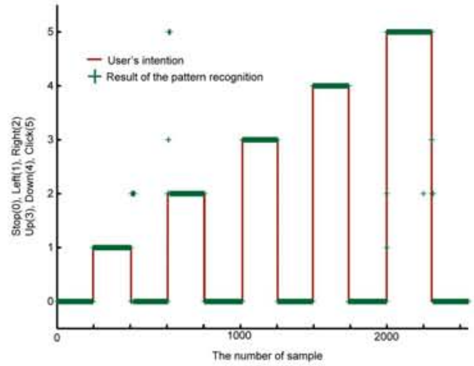

Fig. 5. Result of pattern classification by the maximum selector

III. Results

EMG signals were measured from the muscles (FCU, ECR, ECU, and APL) in the lower arm of the subject as he executed different wrist motions during a 20 second period, as shown in Fig. 4. The obtained signals were filtered, and a supervised multilayer neural network was thereupon used for classification of the user's intended motion. Fig. 5 depicts the results of the pattern classification, where a red solid line denotes the subject's intended motion and green cross marks are the recognized results in numerical values (0-5). Table II reports the success rate of the pattern classification; all patterns are classified above 96.00 %. Considering the failure rate, misclassification occurs mostly during transition in wrist motion, as illustrated in Fig. 5.

From the Fitts' law test, the IP of our interface was found to be 1.341 bit/s. On the other hand, the overall IP of the mouse was 7.743 bit/s. For reference [19], Pino *et al.* evaluated the performance of a commercial assistive pointing device, Brainfingers™ (Brain Actuated Technologies [20]), and the IP of the computer pointing device was 0.386 bit/s.

TABLE II
Success rate of the proposed classification method for discrimination of subjects' intention

	S1	S2	S3	S4	S5	Overall
Stop (%)	97.45	97.68	99.47	98.08	97.18	97.97
Left (%)	97.28	90.47	99.47	96.76	97.76	96.95
Right (%)	98.47	98.55	96.27	94.73	94.49	96.50
Up (%)	99.48	94.22	99.94	96.12	91.28	96.21
Down (%)	99.69	95.94	99.53	99.83	93.35	97.67
Click (%)	99.47	92.33	96.75	99.74	97.18	97.10

IV. DISCUSSION

Some commercial assistive computer pointing devices have been developed, but there very few works have evaluated their usability. Brainfingers™ (Brain Actuated Technologies), a commercial assistive pointing device based on EMG and EEG, was evaluated by employing a Fitts' law test [19]. However, its efficiency was approximately 20 times lower than that of a mouse in terms of IP. From this point of view, since the IP of our interface was three times higher than that of this commercial assistive computer pointing device, development of the proposed interface would contribute to reducing the gap between efficiencies of a mouse and assistive pointing.

However, the efficiency of our interface is still incomparable with that of a mouse. One of the reasons is that the velocity of the cursor is constant, which can be inefficient if the cursor is located far from the target. Also, the movement of the cursor is restricted to only four directions (horizontal and vertical movements). Hence, a more intelligent technique is required to enable greater range in velocity and direction of the cursor movement from EMG signals.

Furthermore, all subjects reported fatigue in their lower arm during the experimental test, because strong wrist motions are required to discriminate classes of motions within the noise effect. This implies that our computer interface is still plausible for long-use application. Therefore, the EMG signal measurement techniques should be further developed to capture even small body motions. This aspect is of particular importance in the development of an HCI for the limb disabled, because their signals are weaker than people with intact limbs.

V. CONCLUSIONS

This paper reported on an EMG-based computer interface that provides schemes to control a cursor and to enter text on a computer. In order to extract the user's intention, EMG signals were acquired from four muscle sites in the lower arm, produced by wrist movements. From these signals, after signal processing for low-pass filtering, six classes of wrist movements were discriminated by employing a multilayer neural network trained by a backpropagation algorithm. In addition, an on-screen keyboard, similar to that used on a mobile phone, was designed so that users can enter Roman and Korean letters on the computer. The developed EMG-based HCI provides an alternative means for the upper limb disabled to access a computer without standard computer interface devices (e.g. a mouse and a keyboard). A possible extension of our interface method can be used to control various platforms such as bionic robot systems for the limb disabled (e.g. exoskeletons, limb prostheses).

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