Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Comparison Study of Biosignal based Computer Interfaces Based on Fitts' Law Paradigm

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Abstract: This paper presents development of two different biosignal based computer interfaces for people with motor disabilities: 1) electromyography (EMG)-based computer interface (ECI) and 2) hybrid EMG-based computer interface (HECI). The ECI made both movements of a cursor and clicking from muscle contractions induced by volitional wrist movements. On the other hand, the HECI made movements of a cursor from the lower arm movements under a motion capture camera, and clicking from muscle contractions induced by volitional movements of index and middle fingers. These interfaces were tested by the experiments based on a Fitts' law paradigm in order to provide object evaluation of the interfaces. These results were also compared to a commercial brain computer interface was evaluated under the same test setup.

1. INTRODUCTION

The standard computer interfaces such as keyboard or mouse are inherently driven by physical contacts (pressure) and movements of users. These physical interactions involve delicate and coordinated movements of upper limb, wrist, palm and fingers. On the contrary, there are the cases, in which some people are not apt to utilize the interfaces with their physical disabilities that have come from diseases such as spinal cord injury (SCI), paralysis, and amputation. In modern days like today's, they involve themselves in projects to restrain the ongoing increase in inconvenience of the uses of the interfaces due to the disabilities. The Ministry of Health and Welfare in South Korea estimated in 2005 that in Korea approximately one million people suffered motor disabilities, and the number has been steadily increasing since 1995. Also, more than 500,000 individuals are living with SCI in North America and Europe (Guertin, 2005).

The alternatives, which modern technology has resolved to, to provide the access to a computing environment for people with the disabilities are direct contact devices with a physical keyboard, such as mouth-sticks and head-sticks. Downsides of these devices are in their inaccuracy and inconvenience in its usage. To overcome those problems, several biosignal based human-computer interfaces (HCIs) have become the new destination of the resolution, which have successfully emerged to extract a user's intention because these signals provide information related to body motion faster than other means (such as kinematic and dynamic interfaces).

Despite the success of the biosignal based HCI, few common standards for the performance evaluation has been established by researchers. They follow the same basic techniques in the development of interface; however, the standards vary greatly among them that it is hard for the people to compare the performance of the different interfaces. Thus, the performance evaluation of the biosignal based HCIs needs to be standardized.

Such standardization will enable the researchers to perform easy and reliable evaluations of the biosignal based HCIs despite the differences in the biosignal sources (such as brain and muscle) and signal processing method (such as feature extraction and pattern recognition) among them. Furthermore, such standardization would help the users of the interface to choose the best fitting assistive interfaces to complement their disabilities without going through time-consuming process of accustoming themselves to the different biosignal sources and complicated signal processing methods of each interface. The development and performance evaluation of the biosignal based HCIs under the standard test setup should initiate better analysis of the each interface as well as a better comparative analysis between the interfaces. Through the comparison and evaluation, computer interfaces can undergo refinements, result in better performance, and allow the physically challenged people to make best decisions.

This paper presents a comparative study of the three different biosignal based computer interfaces under a standard test setup designed by the researcher, who have based their test setup on a Fitts' law paradigm (which is a quantitative model to evaluate the effectiveness of a computer pointing device). Among the three interfaces, two kinds of the interfaces were developed: 1) EMG-based computer interface (ECI) and 2) hybrid EMG-based computer interface (HECI). The ECI processes the movement of a cursor and its clicking s with the signals from the volitional wrist movements and its muscle contraction. On the other hand, the HECI processes movements of a cursor with signals from the perception of the movements of a forearm by a motion capture camera and clicking with the signals from the volitional movements of index and middle fingers and their muscle contractions. The third interface is the brain computer interface available in the market, and this interface has been evaluated in the literature (Pino et al., 2003) under the standard test setup of our evaluation experiment. In addition, a computer mouse, as a standard computer pointing device, which people with intact limbs widely use, was also evaluated under the same test setup.

2. EMG-BASED COMPUTER INTERFACE (ECI)

2.1 System Description

Fig. 1 shows a block diagram of the developed EMG-based computer interface. Only EMG signals were used for transmission from user's intention to a computer using noninvasive surface electrodes (DE-2.1, Delsys) and a data acquisition board (PCI 6034e, National Instrument™). The signals were sampled at 1 kHz and amplified 1000 times, and this interface was developed with Microsoft Visual C++ 6.0.

The target muscles for acquiring EMG signals should be the ones that a user can easily elicit the signal and at the same time the ones related to the motion that can be intuitively mapped to computer operating commands. Under this criterion, four different wrist movements (namely radial deviation, ulnar deviation, wrist extension, and wrist flexion) were chosen by which the user's intention could be expressed, and these movements were mapped to cursor movement commands (i.e. "LEFT", "RIGHT", "UP", and "DOWN"). In addition, the motion of finger extension was mapped to "CLICKING" of a mouse button and rest was mapped to "STOP". Four muscles related to the production of the wrist movements above were selected: the flexor carpi ulnaris (FCU), the extensor carpi radialis (ECR), the extensor carpi ulnaris (ECU), and the abductor pollicis longus (APL) (Perotto, 2005), and EMG signals were recorded as shown in Fig. 2 (a) and (b).

2.2 Signal Processing

It is well established that the EMG signal can be modeled as a zero mean Gaussian process (Shwedyk et al., 1977). Thus, the following equation is used to easily estimate the variance of the signal for feature extraction and low-pass filtering:

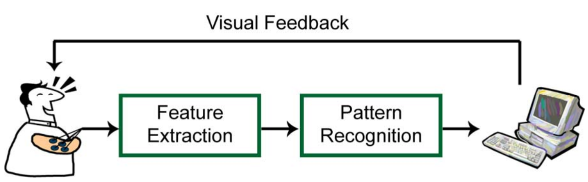
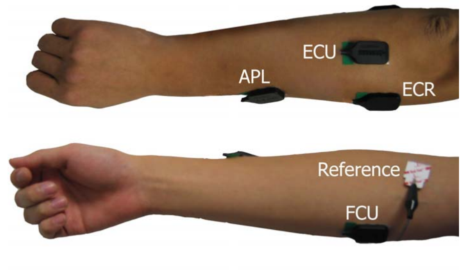
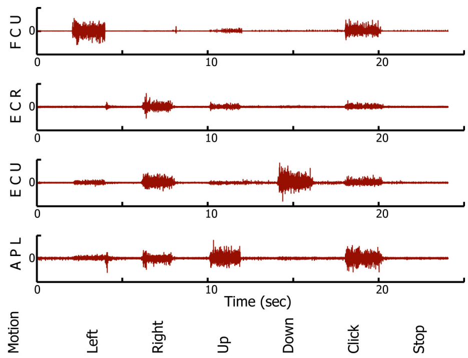


Fig. 1. Block diagram of the developed EMG-based computer interface.



(a)



(b)

Fig. 2. (a) Myoelectric sites for the extraction of EMG signals. Four muscles were selected to extract volitional motor activities: the flexor carpi ulnaris (FCU), the extensor carpi radialis (ECR), the extensor carpi ulnaris (ECU), and the abductor pollicis longus (APL). The images of wires were removed for clear expression of the electrode placement. (b) Recorded EMG signals.

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

where M_i, N, and $\bar{M}$ are the magnitude of the i^{th} signal, the length of an analysis window, and the mean of the magnitude of the N signal data, respectively. The function form of variance is analogous to a moving average filter except for a square term and a denominator.

Since the function of variance is similar to the function of a moving average filter, the cut-off frequency f_c of the low-pass filtering used here can be defined in relation to a moving average filter as follows (Smith, 1999):

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

where f_s is the sampling frequency. This equation describes if a large window is used the effectiveness of the low-pass filtering could be increased (because a cutoff frequency could become smaller). Since noise on the high frequency is, therefore, effectively reduced, this large window helps the accuracy of pattern recognition get higher (Englehart and Hudgins, 2003). However, this large window introduces a significant time delay and thus this delay could be a barrier for a natural real-time computer interface. Hence, there is a

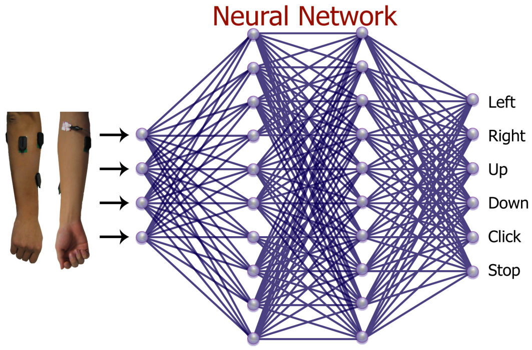


Fig. 3. The structure of the artificial neural network with two hidden layers and ten hidden neurons (for each layer). Six neurons are located at the network's output, and each neuron corresponds to each volitional command to control a cursor movement or clicking.

tradeoff between the real-time signaling and the accuracy of pattern recognition.

Recently, "optimal controller delay" have been suggested for collection and analysis of EMG data to maximize classification accuracy without affecting performance, and the maximum amount of time lied between 100 and 125 ms (Todd and Richard, 2007). Taking into account this experimental result, the length of an analysis window was determined as 100 ms. Thus, this signal process not only provides effective low-pass filtering (f_c = 5 Hz) but also prevents any significant delay.

2.3 Pattern Recognition

Artificial neural network (ANN) has been emerged as an important tool for pattern recognition mainly used in HCI researches (Barniv et al., 2005, Hiraiwa et al., 1990). One of the advantages of using ANN is that because ANN acts like a black box model, it does not require detailed information regarding to the system. In order to design the network (the black box) for the classification of EMG signals, a set of examples flow through the network. Then, the network adjusts its internal structure until it reaches a stable stage at which the outputs are considered satisfactory. After the successful training, the network is preserved and receives new input information, which have never seen before, and then the network processes the information to produce appropriate outputs.

Table 1. Target vectors to classify a user's intention

Class of the volitional command	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 depicts the designed structure of ANN with two hidden layers and ten hidden neurons (for each layer) used in this computer interface. During the training stage, all subjects were instructed to get six different wrist motions in turn, and then the filtered EMG signals were extracted. Next, the network was trained using those six groups of wrist movements and desired network responses shown in Table 1. Its tuning was carried out by using a backpropagation algorithm with a momentum approach.

3. HYBRID EMG-BASED COMPUTER INTERFACE (HECI)

3.1 System Description

Fig. 4. shows a block diagram of the developed hybrid EMG-based computer interface. For the movements of a cursor, a motion track system (Micron Tracker, Claron Technology Inc.) was used to track a marker attached on a single forearm. Two dimensional movements of the arm were mapped directly into the cursor movements. For the clicking command, extensions of index and middle finger were used and these two different finger movements are able to bring out two different clicks like "Left/Right Button Clicks" on a computer mouse. These two finger movements were caught from observation of extensor digitorum (ED) muscle contractions. This muscle divides distally into four tendons which pass in a common synovial sheath with the tendon of extensor indicis, and through a tunnel under the extensor retinaculum and diverge on the dorsum of the hand, one to each finger (Gray et al., 2005). Therefore, two fingers' movements are anatomically dependent, but the independent finger extensions are observable by attaching separately two EMG electrodes regarding of locally separate contractions. Fig. 5(a) shows the developed hybrid EMG-based computer interface setup, and EMG signal were recorded as shown in Fig. 5(b).This interface was developed with Microsoft Visual

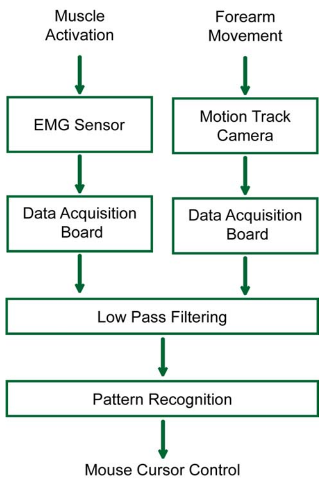


Fig. 4. Block diagram of the developed hybrid EMG-based computer interface.

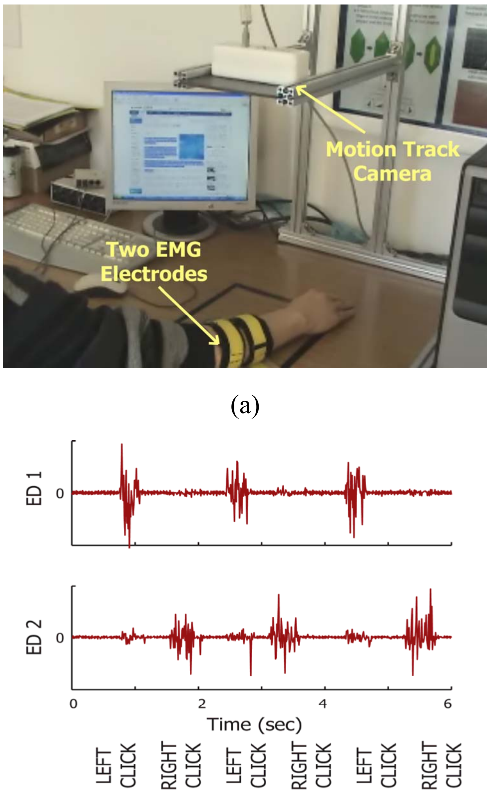


Fig. 5. (a) The developed hybrid EMG-based computer interface setup. (b) Recorded EMG signals.

C++ 6.0.

3.2 Signal Processing

To track the position of the forearm from a camera, the tracking coordinate was updated at 20 Hz, and this three dimensional coordinate was transformed into a two dimensional coordinate removing depth information between the arm and the camera. Since this tracking data include some random noise from image, they slightly change at the rate even though a use's forearm does not move. When the tracking data was used directly to move a cursor without any signal processing, the cursor trembles on a computer screen. However, people do not want to let move a mouse to control a cursor while reading and watching something through the monitor because it could disturb to concentrate on doing them. Although the small amount of noise affected the tracking data, it made the small trembles of the cursor, and even its one pixel change at the every time could be a problem. To avoid this tremble, a simple low pass filter was used:

$$\bar{x} = \sum_{i=1}^{N} \frac{x_i}{N} \tag{3}$$

where x_i, $\bar{x}$, and N are of the i^{th} motion signal, the average of the signals, and the length of an analysis window, respectively. For EMG signal processing, the same method was used as the section 2.2 in this paper.

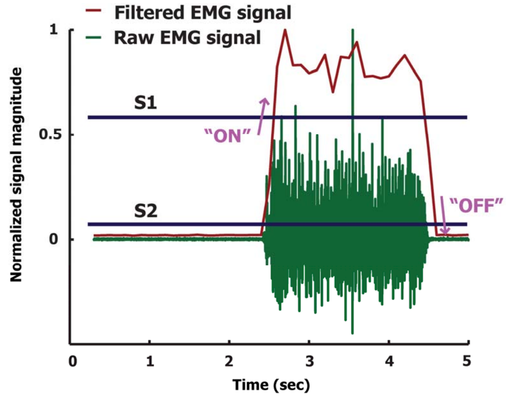


Fig. 6. An example of one channel amplitude-coded myoelectric control.

3.3 Pattern Recognition

If many movements of the body motion are estimated from muscle contractions, sophisticated means of discriminating different muscle states could be required. That is because each body motion cannot be matched with each muscle contraction like one by one, and also coherent contractions in space or in time of a group of muscles occur to produce even one simple body movement. However, in the developed interface, because two channel EMG signals were used, a sophisticated classifier was not required and also it could be time-consuming work on the real-time point of view. Therefore, a simple classification method was implemented in this interface, which detects whether a muscle is contracted like "ON or OFF state."

Fig. 6 depicts an example of EMG signals with two different states from one when a muscle is relaxed to the other when a muscle is fully contracted, and these ranges can be spatially divided. To discriminate these spaces on the graph, two thresholds, S1 and S2, were determined empirically and S1 must be larger than S2. When the filtered signal is greater than S1, it means a muscle is fully contracted, "ON," and otherwise when the filtered signal is smaller than S2, it means a muscle is relaxed, "OFF." The "ON" state was matched with the command, "MOUSE BUTTON DOWN," and The "OFF" state was matched with the command, "MOUSE BUTTON UP." Using this amplitude-coded myoelectric control, it is possible to implement several useful functionalities like them of the computer mouse: such as "DOUBLE CLICKING" and "DRAGING." In contrast to the EMG signal, the motion track signal did not need to go through pattern recognition process, because the recorded signal was directly transferred into the movements of the cursor.

4. EXPERIMENTAL SETUP ON A FITTS' LAW PARADIGM

Fitts' Law (Fitts, 1992, Fitts and Peterson, 1964) is a quantitative model to evaluate the effectiveness of a

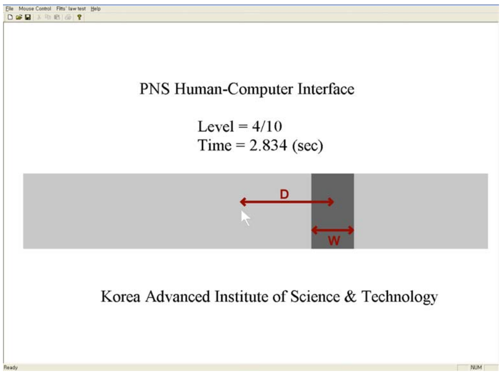


Fig. 7. Snapshot of the testbed on a Fitts' law paradigm.

computer pointing device and also to compare novel pointing device with the others (for a review of the Fitts' Law; see (MacKenzie, 1992)). Since 1954 when the Fitts' Law was presented, this model has been used successfully in HCI area, and has undergone some refinements in its mathematical formulation. Now, this model becomes one of the cornerstones in performance evaluation of a computer pointing device.

In our experiment, the protocol used a Fitts' Law paradigm, and this evaluation was conducted into three sorts: the first and second sessions were for the use of the developed interfaces and the other session was for the use of a computer mouse (a standard computer interface tool). Even though people with the disabilities cannot use a mouse, the purpose of this comparison is in an effort to investigate where the developed interface is relatively to a standard computer interface which people with intact limbs have widely used. Seven subjects (S1-S6: S1-S5 were for the ECI evaluation and the mouse evaluation, S5-S6 were for the HECI evaluation) with intact limbs (5 males, 26.17 years of age) volunteered. A testbed was designed for the experimental test shown in Fig. 7. The subjects were instructed to point and to click on a target (a dark rectangle) by moving a cursor, and time (movement time, *MT*) was measured taken to complete the task. The difficulty of the task depends on the width of the target *W* and the distance *D* between the cursor and the target. To mathematically express the difficulty, the Shannon formulation of the index of difficulty (*ID*) was used (Accot and Zhai, 1997), and the *ID* is expressed in "bits" as follows:

$$ID = \log_2\left(\frac{D}{W}+1\right) \tag{4}$$

Thus, the task becomes more difficult as *D* increases and *W* decreases. In this experiment, three different widths (*W* = 30, 70, and 110 pixels) and three different distances (*D* = 150, 300, and 450 pixels) were selected in line with Pino *et al.* (Pino et al., 2003), who evaluated the performance of a commercial assistive pointing device called Brainfingers™ (Brain Actuated Technologies), based on Fitts' Law. According to Fitts' Law, *MT* and *ID* have the following linear relation:

$$MT = a + b \cdot ID \tag{5}$$

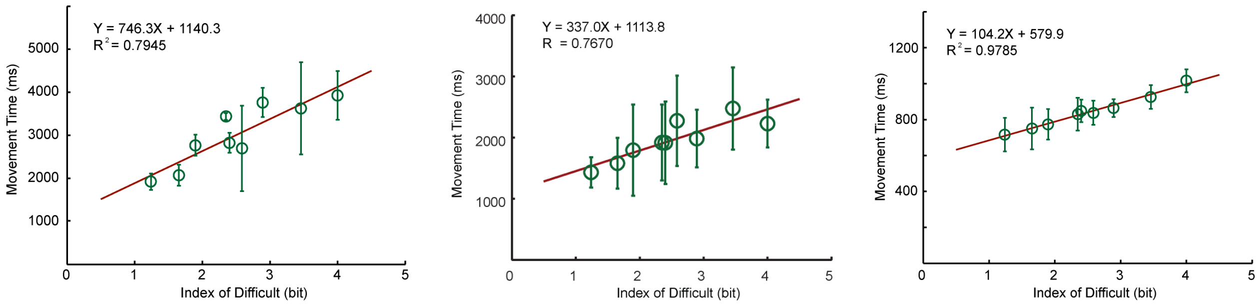
In this form, a reciprocal number of *b* is in "bits/s" and is called the index of performance (IP) or bandwidth. The IP represents how quickly the pointing and clicking can be done with the computer pointing device. Namely, an interface with higher IP is better than that with lower IP, because high IP indicates that the less *MT* is affected the greater *ID* increased.

The position of the target in this experiment was randomly assigned for each session so that a user does not expect it. Then, the cursor was positioned on the right side or the left side of a target in accordance with the *ID* of each session. At the beginning of the experiment, all subjects were instructed to click a dummy target and then to click nine targets with different *ID*s. The duration of the pointing and clicking at each session was measured, and this process was repeated as 20 times per subject.

5. RESULTS AND DISCUSSIONS

Fig. 8 shows that the experimental data of the *MT* and the *ID* for a subject have a linear relationship in accordance with Fitts' Law. From this relationship, IPs of the developed interfaces were acquired: 1.299 bits/s for the ECI and 3.047 bits/s for the HECI, and IP of the mouse was 7.733 bits/s. The IP of the mouse we achieved is comparable to the literatures where Pino *et al.* and Zhai *et al.* have reported the IP value of the mouse as 7.048 and 8.445 bits/s (Pino et al., 2003, Zhai et al., 2003).

Pino *et al.* have evaluated the performance of a commercial



(a) (b) (c)

Fig. 8. Relation between the movement time (MT) and the index of difficulty (ID) from the experiment on a subject: (a) the developed EMG computer interface, (b) the developed hybrid EMG computer interface, and (c) the computer mouse. The gentle slope of the line illustrates the high IP (index of performance) value.

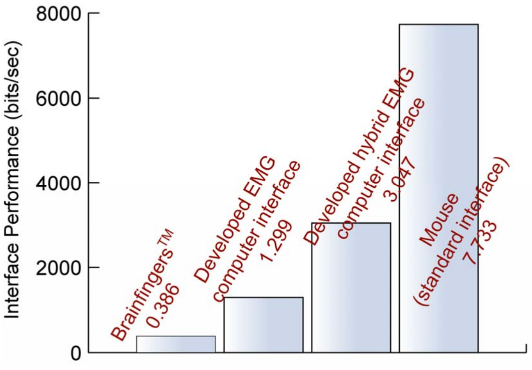


Fig. 9. A comparison plot showing interface performance

assistive pointing device called Brainfingers[TM] (Brain Actuated Technologies) under the same test setup based on a Fitts' law paradigm, and the IP was 0.386 bits/s (Pino et al., 2003). The HECI has the greatest IP among the biosignal based interfaces mentioned here, and performance of the HECI is approximately 8 times greater than that of the commercial assistive computer pointing device, which means our development of the interface reduced the gap in efficiency between a mouse and an assistive pointing device.

Fig. 9 shows the comparisons of the performance results among four computer interfaces. The HECI, however, was not still able to achieve the performance comparable with the mouse (IP = 7.733 bits/s) in terms of the performance evaluation results.

6. CONCLUSIONS

This paper presents a quantitative comparison study of three different biosignal based computer interfaces for the people under the same test setup based on a Fitts' law paradigm for people with motor disabilities to access a computer comfortably. Even though our development of the interface reduced the gap in efficiency between a mouse and an assistive pointing device, it is still less efficient than the mouse.

Future works will go in the direction of developing assistive computer interface with consideration for how a cursor could be more efficiently controlled. For this purpose, the performance result we achieved here will be analyzed using a design tool, and then factors why performance of the HECI is better than the other assistive interfaces could be found. In considerations of those factors, a new assistive computer interface in high efficiency could be designed for people with motor disabilities.

ACKNOWLEDGMENTS

The work described here was supported by the IT R&D program of MIC/IITA [2005-S-096-02, Development of wearable PC interface technology for the disabled].

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