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Development and Performance Evaluation of a Neural Signal Based Computer Interface

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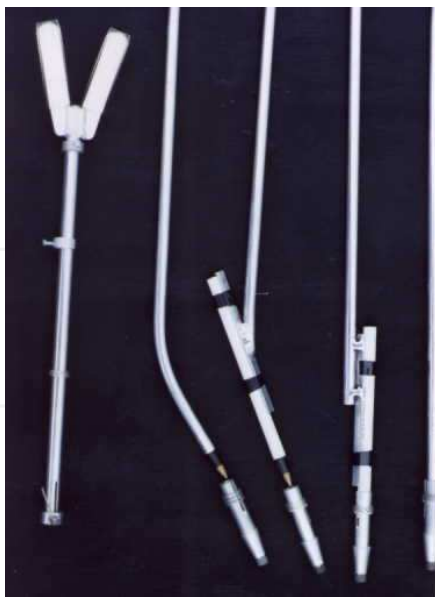
1. Introduction

The use of personal computers has drastically increased since the 1990s, and they have been responsible for tremendous achievements in information searching (Internet browsing) and communication (e-mail) around the world. People commonly use standard computer interfaces such as the keyboard and mouse, which are operated through physical contact and movement. These physical interactions inherently involve delicate and coordinated movement of the upper limb, wrist, palm, and fingers. However, there are some people who are not capable of using these interfaces because they have physical disabilities such as spinal cord injuries (SCIs), paralysis, and amputated limbs. In 2005, the Ministry of Health and Welfare in South Korea estimated that there were approximately one million people suffering from motor disabilities in South Korea, and the number has been steadily increasing since 1995. It has also been reported that more than 500,000 individuals are living with SCIs in North America and Europe (Guertin, 2005). If people with disabilities could access computers for tasks such as reading and writing documents, communicating with others, and browsing the Internet, they could become capable of a wider range of activities independently.

Alternative methods for providing individuals with disabilities access to computing environments include direct contact with physical keyboards, such as that shown in Fig. 1 (a); i.e., through the use of mouth sticks and head sticks. However, these devices have the disadvantage of being inaccurate and inconvenient to use. Another notable computer interface is the eye-movement tracking system, shown in Fig. 1 (b). This interface can perform as fast as, or even faster than, a mouse (Sibert & Jacob, 2000). This is because eye-gaze supports hand movement planning (Johansson et al., 2001); therefore, signals due to eye movement are quicker than those due to hand movement. Eye movements, however, as with other passive and non-command inputs (e.g., gestures and conversational speech), are often neither intentional nor conscious. Therefore, whenever a user looks at a point on the computer monitor, a command is activated (Jacob, 1993); consequently, a user cannot look at any point on the monitor without issuing a command. The eye-movement tracking system thus brings about unintended results.

Currently, biomedical scientists are making new advances in computer interface technology with the development of a neural-signal-based computer interface that is capable of directly bridging the gap between the human nervous system and the computer. This neural

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(a) Mouth stick

(<http://www.mouthstick.net/>)



(b) Eye-gaze interface

(http://www.brl.ntt.co.jp/people/takehiko/fr_eegaze/index.html)

Fig. 1. Alternative computer interfaces for people with physical disabilities.

produce neural signals, because the signals naturally accompany body movements. Second, in this interface, neural signals are produced prior to actual body movements, and thus, the interface is even faster than kinematic and dynamic devices such as force sensors and motion trackers (Cavanagh & Komi, 1979). Such neural interfaces are classified into two categories on the basis of the signal source arriving from the central nervous system (CNS) or the peripheral nervous system (PNS).

Interfaces based on CNS signals, specifically signals from brain activity, have the potential to reveal human thought and are called brain-computer interfaces (BCIs). The major advantage of a BCI is that people with extremely severe motor disabilities such as quadriplegics can access a computer. An electroencephalogram (EEG), which measures brain activity recorded by electrodes placed on the scalp, is a good example of the use of CNS signals (Cheng et al., 2002; Citi et al., 2008; Kennedy et al., 2000; McFarland et al., 2008; Millan Jdel et al., 2004). For end users, the EEG's primary advantage is that it is noninvasive; however, this often results in a low signal-to-noise ratio (SNR), which in turn results in difficulties in accurately representing the users' intentions. In addition to the EEG signals, invasive CNS signals have been studied in recent years, and they capture the activity of individual cortical neurons obtained by microwire arrays that have been surgically implanted within one or more cortical motor areas (Hochberg et al., 2006; Taylor et al., 2002; Wessberg et al., 2000). This method provides better SNRs and spatial resolutions than noninvasive methods; in addition, this approach has been used recently with interesting results for selected quadriplegics (Hochberg et al., 2006). However, these invasive methods cause discomfort to the human and bear the risk of infection. Many issues of BCIs need to be addressed regarding brain map reorganization and chronic usability before making this method functional in extensive clinical experiments (Sanes & Donoghue, 2000).

PNS signals, which extend outside the CNS to serve the limbs and organs, can be used to extract user movement intent. A representative PNS signal is that detected by surface electromyography (sEMG), which is the electrical representation of activity produced by a

number of muscle fibers in a contracting muscle and summation of motor unit action potentials. To observe the activities, a sEMG electrode is attached to the skin surface over the muscle; this method avoids any skin incision or percutaneous invasion unlike methods for cortical signal extraction. SEMG has been widely used as an interpretation tool for neural muscular control in neurophysiology studies (d'Avella et al., 2003; Merletti et al., 1999) and rehabilitation (Dipietro et al., 2005; Veneman et al., 2007), and also as an interface tool to detect movement intention of the end user in conjunction with artificial prostheses (Chu et al., 2007; Cipriani et al., 2008) and teleoperation (Fukuda et al., 2003).

In this chapter, we discuss a sEMG-based computer interface that allows people with amputations or SCIs to access a computer without using standard interfacing devices (e.g., a mouse and keyboard). Using the developed interface, a user can move a cursor, click a button, and type text on the computer using only their wrist movement. Furthermore, the efficiency of the interface was quantitatively measured using the Fitts' law paradigm, and the performance of this interface was compared with performances of currently used interfaces using the same test setup and conditions.

2. Materials and methods

2.1 Computer interface overview

The interface was designed to concurrently measure the sEMG signals and control a mouse cursor on a computer screen, as shown in Fig. 2. The activities of four muscles were recorded and amplified 1000 times by bipolar noninvasive surface electrodes (DE-2.1, Delsys, USA) with built-in amplifiers. The electrodes were connected to a data acquisition board (PCI 6034e, National Instruments™, USA), which transmitted the signals to a computer at 1000 Hz. Features were extracted from the measured signals by reducing the randomness of sEMG signals (referred to as feature extraction) and were fed into a pattern recognition program to classify the body movements. The classified movements were translated into predetermined commands and consisted of two-dimensional movements and clicking of a cursor to use the computer. Finally, the cursor was moved or a button was clicked on a computer screen using the classification results, and these processes were repeated by the volitional motor activities of the user with visual feedback.

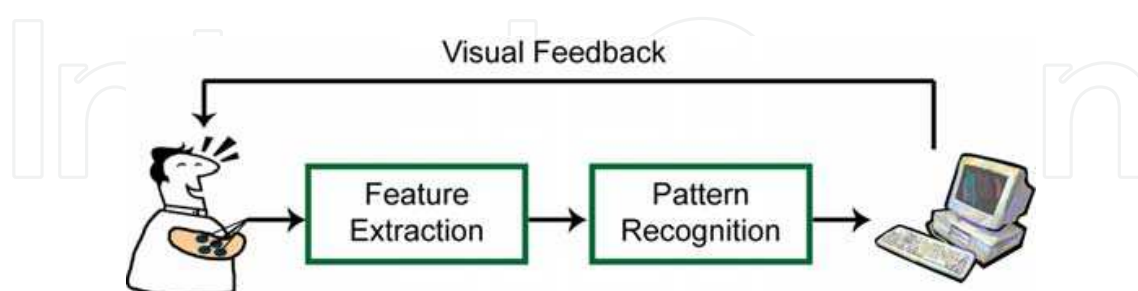


Fig. 2. Computer interface overview.

2.2 Motion and muscle selection

The selection of the target muscles to be used to obtain the signals must satisfy both ease of mapping the signals to computer operating commands and clear observability of the signals on the skin surface. To map the signals to the commands, four different wrist movements (wrist flexion, wrist extension, radial deviation, and ulnar deviation) were chosen, and these

movements were mapped to the cursor movement commands (LEFT, RIGHT, UP, and DOWN). The user can intuitively control the cursor through these movements because the direction of the wrist movement corresponds to the direction of the cursor movement. In addition, to CLICK a mouse button and then STOP this movement, the movements of the hand such that it is open (coactivation of the muscles) and at rest were selected, respectively. When the user flexes his/her wrist (wrist flexion), the cursor moves to the left. To maintain the movement, the user must maintain the wrist flexion. The STOP condition occurs when the cursor does not move. Therefore, if the user wants to stop the cursor's movement, he/she should return and maintain the neutral position of the wrist. To observe the cursor movements, four muscles that produce the chosen wrist movements were selected: the flexor carpi ulnaris (FCU), the extensor carpi radialis (ECR), the extensor carpi ulnaris (ECU), and the abductor pollicis longus (APL), as shown in Fig. 3. Their activities were easily observable on the skin surface.

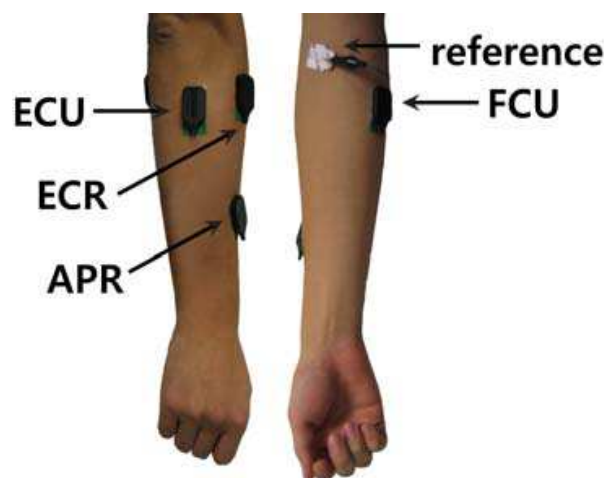


Fig. 3. Myoelectric sites for the sEMG signal extraction. Four muscles were selected to extract volitional motor activities: the flexor carpi ulnaris (FCU), the extensor carpi radialis (ECR), the extensor carpi ulnaris (ECU), and the abductor pollicis longus (APL). Wires were removed from the image for clear expression of the electrode placements.

2.3 Feature extraction

The electrophysiological phenomena at the cell membrane reflect the active state of living cells (Rau et al., 2004). In this sense, sEMG is related to the complex activation of skeletal muscles that results in static and dynamic active force exertion and movement control. The information obtained from sEMG should quantitatively represent the activation of skeletal muscles and highly correlate to the muscle force. Feature extraction (Zecca et al., 2002) converts a raw sEMG signal (which is obtained immediately after the amplification of the signal from the sensor) to a smoothed signal (called also an envelope) related to muscle force or voluntary driving of a muscle.

SEMG signals have been commonly regarded as Gaussian random process, and Hogan and Mann (1980) theoretically showed that the root mean square (RMS) processing shown in equation (1) is a maximum likelihood estimator of the sEMG signal when the magnitude of the raw sEMG signal has a Gaussian distribution.

$$\text{RMS} = \sqrt{\frac{\sum_{i=1}^N (M_i - \bar{M})^2}{N-1}} \quad (1)$$

where M_i , N , and \bar{M} are the magnitude of the i^{th} data element, length of the analysis window, and mean of the magnitudes of N data respectively. The function of variance is analogous to a moving average filter excluding the root square term and denominator.

As a moving average filter, the cut-off frequency, f_c , of the low-pass filter was defined in relation to a moving average filter as follows (Smith, 1999):

$$f_c = \frac{f_s}{2N} \quad (2)$$

where f_s and N are the sampling frequency and the analysis window length, respectively. This equation describes how the effectiveness of the low-pass filter increases with a larger window because the cutoff frequency decreases. Since high-frequency components in the signals are effectively reduced, a large window increases the accuracy of the pattern recognition (Englehart & Hudgins, 2003). In contrast, a large window introduces a significant time delay and this delay could become an obstacle for a natural real-time computer interface. Hence, there is a tradeoff between real-time signal processing and the accuracy of the pattern recognition. Recently, Farrell et al. suggested an "optimal controller delay" for the collection and analysis of sEMG signals to maximize the classification accuracy without affecting performance; the maximum calculation time was between 100 and 125 ms (Todd & Richard, 2007). Taking into account this experimental result, the length of the analysis window was set to 100 ms. Thus, the signal processing not only provides effective low-pass filter effects ($f_c = 5$ Hz) but also prevents significant delays.

2.4 Pattern recognition

Artificial neural networks (ANNs), inspired by biological neural networks, have emerged as an important tool for pattern recognition in much human-computer interface (HCI) research (Barniv et al., 2005; Hiraiwa et al., 1990). An ANN is composed of a number of highly interconnected artificial neurons that are activated by external stimuli and is capable of learning key information patterns in multidimensional domains. There are two primary advantages of using an ANN. First, it is possible to classify data without any knowledge of prior probabilities of patterns belonging to one class or another. Second, because an ANN acts as a black box model, it does not require detailed information such as that of the human muscular-skeleton system. To design the classification network, a set of signals are allowed to flow through the network. The network then adjusts its internal structure until it is stable, at which time the outputs are considered satisfactory. After successful training, the network is preserved and receives new input signals, and then the network processes the data to produce appropriate outputs.

Figure 4 illustrates the structure of an ANN with two hidden layers and 10 hidden neurons for each layer for pattern classification of the six different wrist movements. During the training stage, all subjects were instructed to make the movements in turn, and the signals were recorded. Next, the network was trained using the six groups of features with the desired network responses shown in Table 1. Network tuning was performed using a backpropagation algorithm with a momentum approach (Haykin, 1999).

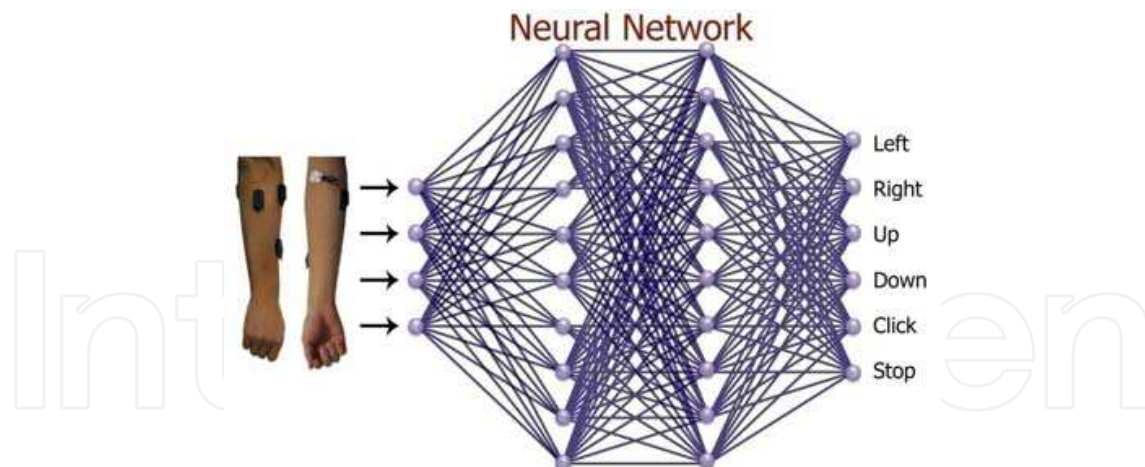


Fig. 4. Structure of the artificial neural network with two hidden layers and ten hidden neurons for each layer. Six neurons are located at the network's output, and each neuron corresponds to a volitional command to control a cursor movement or clicking.

Class of volitional command	Desired network response						
STOP	1	0	0	0	0	0	0
LEFT	0	1	0	0	0	0	0
RIGHT	0	0	1	0	0	0	0
UP	0	0	0	1	0	0	0
DOWN	0	0	0	0	1	0	0
CLICK	0	0	0	0	0	0	1

Table 1. Target vectors for classifying user intentions.

3. Performance evaluation

Fitts' law is a model of human psychomotor behavior derived from Shannon's theorem 17, a fundamental theorem of communication systems (Fitts, 1992), and is the most robust and widely adopted model to emerge from experimental psychology (MacKenzie, 1992). The law reveals an intuitive tradeoff in human movement—the faster we move, the less precise our movements are, or alternatively, the more severe the constraints are, the slower we move. Fitts formulated the tradeoff for three experimental tasks (bar strip tapping, disk transfer, and nail insertion) that are essentially of one paradigm—the hitting of a target over a certain distance. When considering an HCI, this paradigm corresponds to a frequent elemental task—pointing/target selection—and the paradigm can be applied as a predictive model to estimate the time for a user to move a cursor to a button and click it on a graphical interface. It is, therefore, useful to be aware of the effectiveness of a new computer-pointing device and to compare it with others. Since first presented in 1954, Fitts' law has been successfully used in many HCI areas with refinements of its mathematical formulation. It is now a cornerstone of the performance evaluation of pointing devices.

According to Fitts' law, the movement time (MT) required to move a cursor onto a target and the task difficulty (ID, index of difficulty) have the following linear relation.

$$MT = a + b \cdot ID \quad (3)$$

In this form, the reciprocal of b is called the index of performance (IP) and is measured in bits per second (bps). The IP represents how quickly the pointing and clicking can be performed using the computer-pointing device. That is, an interface with a higher IP is better than that with a lower IP, because a high IP indicates that the performance is less affected by a high ID. The ID depends on the width W of the target and the distance D between the cursor and target. To mathematically express this difficulty, the Shannon formulation is used, and the ID is expressed with a unit of bits as follows.

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

Thus, it is obvious that the task becomes more difficult as D increases or 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 previous research (Pino et al., 2003) that evaluated the performance of the commercial assistive pointing device Brainfingers™ (Brain Actuated Technologies, USA), which is based on Fitts' law.

Tests were conducted in two sessions, one each for the developed interface and a mouse (a standard computer interface tool). Five subjects (S1–S5) with intact limbs (five males with an average age of 26.4 years) volunteered and sat comfortably in front of a computer screen that continuously displayed the testbed shown in Fig. 5. The subjects were instructed to point to and click on a rectangular target (a dark rectangle) by moving a cursor, and MT was measured for the task. The targets in this experiment were randomly assigned in each session so that a user could not predict their locations, and the cursor was positioned on the right or left side of the 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 click nine targets with different IDs. The duration of the pointing and clicking for each session was measured, and this process was repeated 20 times for each subject.



Fig. 5. Snapshot of the testbed for performance evaluation of the developed computer interface.

4. Results

In Fig. 6, the top graphs show the raw recorded sEMG signals from the four muscles (FCU, ECR, ECU, and APL) on the lower arm of the subjects and the bottom graphs represent the features extracted using RMS processing. It is evident that each feature set of the five different computer commands is characterized well for the classification. The features were entered into the ANN as input data, and Fig. 7 shows the ANN output values between 0 and 1. At the end of the ANN, a maximum selector chose the neuron with the largest value, and the neuron was directly matched to the computer commands, as shown in Fig. 8. Recognition accuracy was tested using the same subjects who took part in the Fitts' law test, and Table 2 summarizes the results. All movements were successfully classified, at a rate of

over 96% accuracy, and misclassification usually occurred during the period of transition from one gesture to another. In Fig. 6, when a subject had a wrist flexion (LEFT), the FCU muscle was mainly activated. At the end of the movement, the other muscles were suddenly activated and Fig. 8 shows the misclassification at that time. This phenomenon can be explained by the transition from a wrist flexion movement to achieving the neutral position requiring a wrist extension movement.

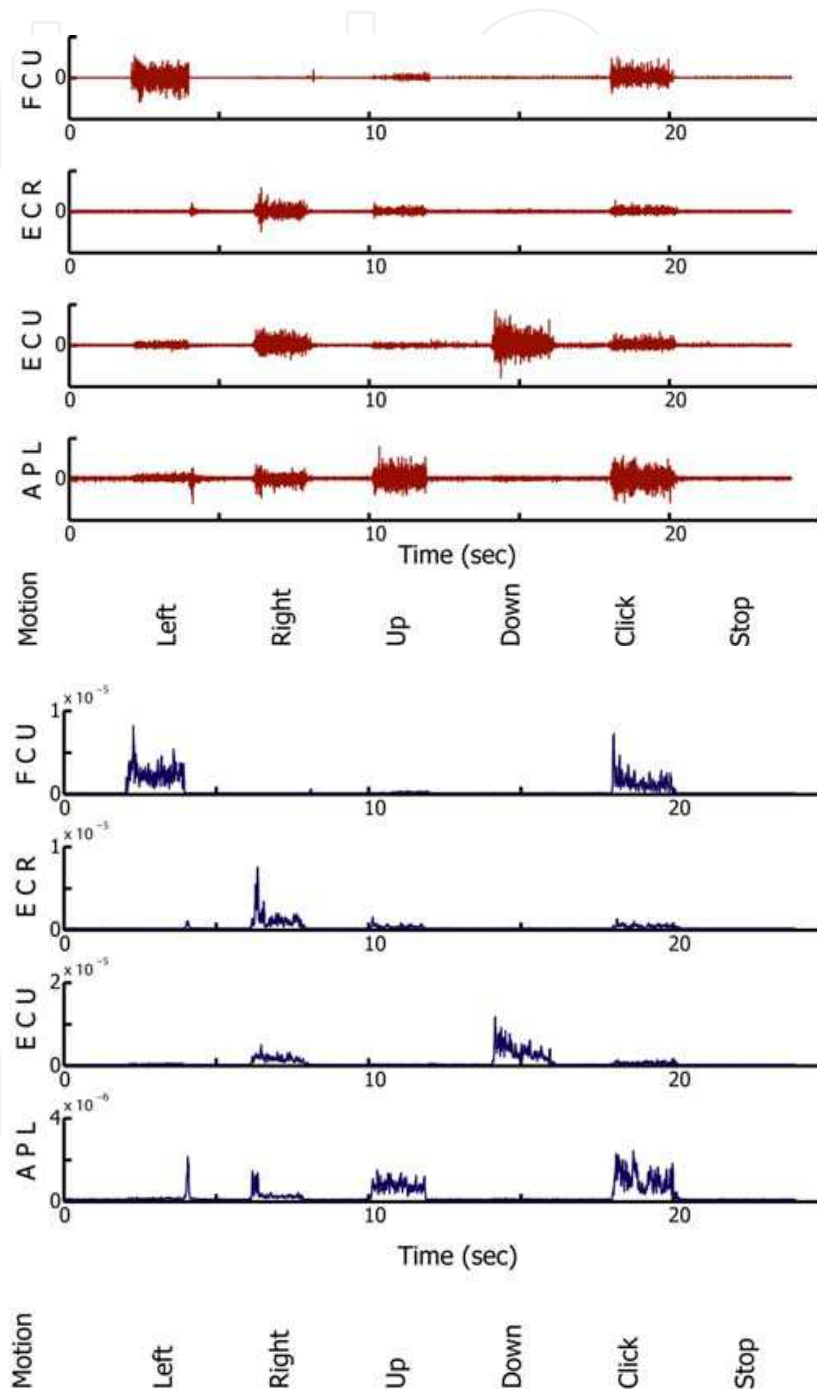


Fig. 6. Recorded raw sEMG signals and their features corresponding to a user's intentions from four muscles: the flexor carpi ulnaris (FCU), the extensor carpi radialis (ECR), the extensor carpi ulnaris (ECU), and the abductor pollicis longus (APL).

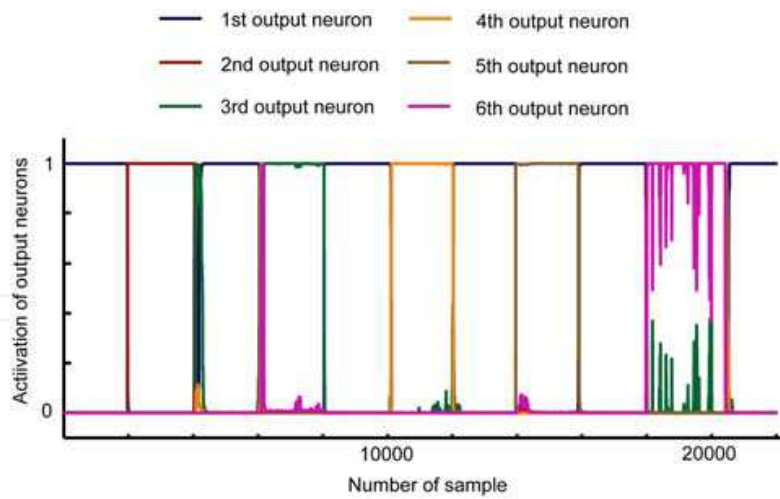


Fig. 7. Output neuron activation at the end of the network.

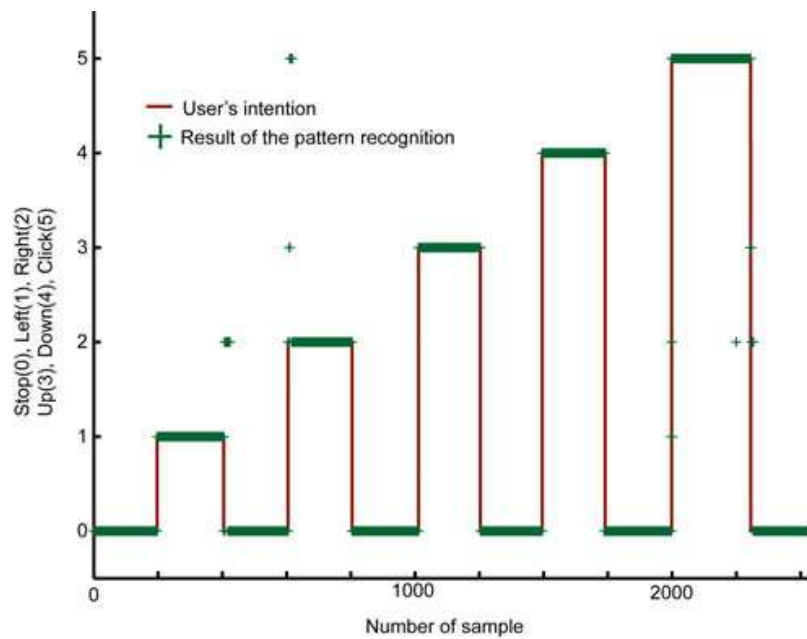


Fig. 8. Pattern recognition results. The red solid line denotes the intended movement of a subject and the green crosses show the recognized results as numerical values 0-5 (0: STOP, 1: LEFT, 2: RIGHT, 3: UP, 4: DOWN, and 5: CLICK).

	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

Table 2. Success rates of the proposed classification method in the discrimination of subject intentions.

Table 3 summarizes the results of the performance evaluation of both the developed interface and the mouse for the five subjects. All movement times were averaged from the 20 data for each subject. Figure 9 shows that the experiment data of the MT and ID for the subject S2 have a linear relationship in accordance with Fitts' law, and the upper and lower lines represent the results for the developed interface and mouse, respectively. From these results, the IP was calculated and is presented in Table 4; the overall IP of the developed

D (pixels)	W (pixels)	ID (bits)	Movement time (MT)									
			Subject 1		Subject 2		Subject 3		Subject 4		Subject 5	
			sEMG	mouse	sEMG	mouse	sEMG	mouse	sEMG	mouse	sEMG	mouse
150	110	1.2410	1920.5	715.9	1520.8	762.7	1925.6	695.8	1729.0	724.9	1664.5	728.2
300	110	1.8981	2770.3	773.2	2443.3	857.4	2693.5	737.7	2466.2	859.6	2480.5	787.9
450	110	2.3479	3437.1	830.0	3175.2	910.5	3251.5	818.4	3479.9	915.8	3578.3	898.2
150	70	1.6521	2073.0	750.4	1680.1	831.4	1881.8	774.1	1717.0	870.5	1762.6	920.1
300	70	2.4021	2825.9	848.3	2536.2	914.2	2557.5	827.6	2614.4	960.0	2656.6	939.6
450	70	2.8931	3763.1	864.1	3186.5	954.2	3353.9	908.2	3338.1	971.0	3630.9	932.9
150	30	2.5850	2694.6	837.7	2366.0	982.2	2007.4	920.8	2721.4	1096.5	2407.1	923.5
300	30	3.4594	3626.5	925.5	3421.5	1081.4	2624.7	957.3	3087.1	1078.0	3255.8	1012.6
450	30	4.0000	3928.0	1015.8	4008.5	1151.0	4221.9	1063.9	3813.3	1215.0	4276.2	1157.0

Table 3. Experiment results of the Fitts' law test for the efficiency of the sEMG interface.

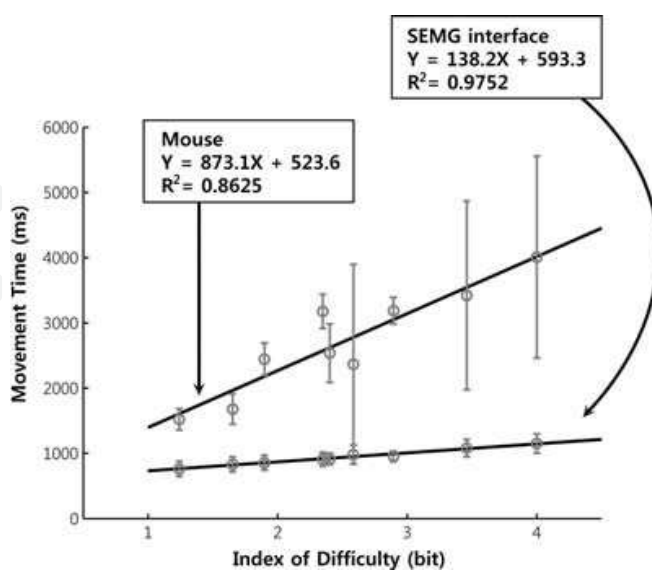


Fig. 9. Relation between movement time (MT) and index of difficulty (ID) from the experiment for subject S2 using a mouse and the developed sEMG computer interface. The gentle slope of the line illustrates the high IP (index of performance) value.

		S1	S2	S3	S4	S5	Overall
sEMG	IP (bps)	1.340	1.145	1.503	1.376	1.129	1.299
	R^2	0.795	0.863	0.554	0.736	0.752	0.740
mouse	IP (bps)	9.600	7.238	7.674	6.343	7.811	7.733
	R^2	0.979	0.975	0.940	0.868	0.824	0.917

Table 4. Experimental results of the efficiency of pointing devices from Fitts' law test using the developed interface and the mouse for five subjects (S1–S5). R^2 is the correlation coefficient.

interface was 1.299 bps, whereas the overall IP of the mouse was 7.733 bps. Pino et al. (2003) and Zhai et al. (2003) reported the IP value of a mouse as 7.048 and 8.445 bps respectively, and thus, the IP value of the mouse obtained in this study is comparable to values in the literature.

5. Discussion and conclusion

The developed interface has the potential to enable people with motor disabilities to interact with a graphic user interface in a natural and intuitive way. The interface was not tested for such individuals; however, it was tested for individuals with bilateral hand amputations and SCIs at the C6–C7 functional levels, who had control of the muscles (FCU, ECR, ECU, and APL). The interface efficiency was quantitatively measured using the Fitts' law test setup, and the performance of the proposed interface was compared with performances of other available interfaces. The ANN of the developed interface provided a high recognition ratio of over 96%, which shows that the computer commands are extracted well from the user. In addition, the IP of the interface was 1.299 bps, compared with the reported IP of 0.386 bps (Pino et al., 2003) for the commercial assistive pointing device Brainfingers. Thus, the performance of the developed interface was approximately three times better than that of the commercial device. The target performance of the alternative interface should be equivalent to the IP of a mouse so that individuals with motor disabilities can use a computer in a manner comparable to people without disabilities. The sEMG interface was, however, not able to perform as well as a mouse; its IP was 7.733 bps. Its performance was between that of a mouse and the commercial interface. Its low efficiency could be attributed to the constant speed of the cursor, which is potentially problematic when the cursor is located far from the target. To solve this problem, a more intelligent technique of producing cursor movements with an adjustable speed is required. A possible feasible way to achieve this is to map the magnitude of the muscular force to speed. However, it is not easy to estimate muscular force. In order to estimate muscular force, the ANN setting should be changed to concurrently estimate both the body movement and muscular force. In addition, cursor movement is restricted to only two directions (horizontal and vertical movements), and it cannot move in a diagonal direction, which has already been mentioned in recent literature (Citi et al., 2008). This issue could be solved if all wrist movements are predicted using 360° of motion, but it is a great challenge to estimate the infinite degrees of freedom in the human muscular–skeletal system.

This study has important implications for future work on the development of assistive computer interfaces, particularly with regard to improving the efficiency of controlling cursor movement. For this purpose, the performance results presented in this paper will be

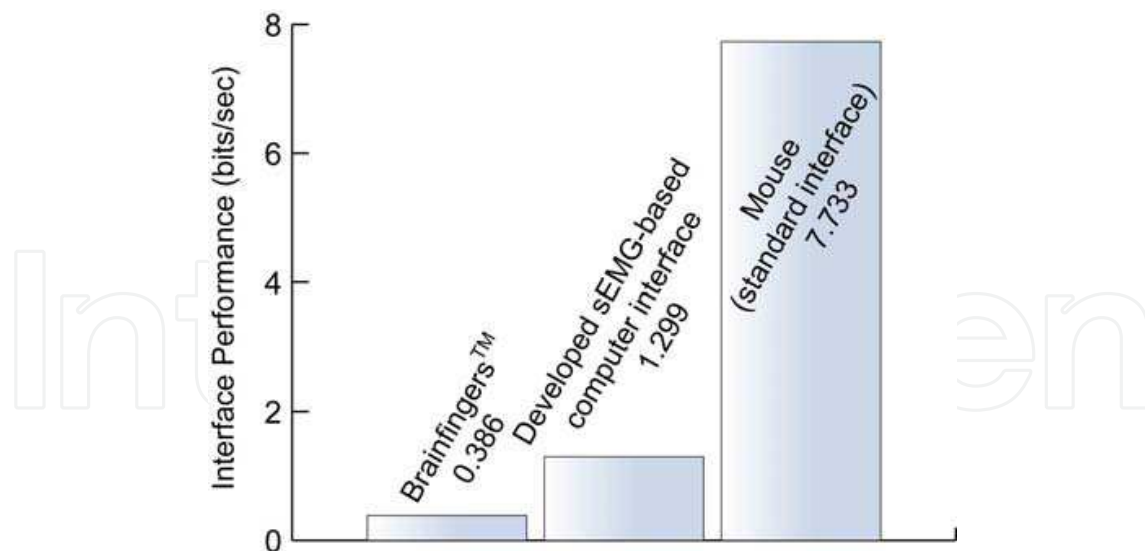


Fig. 10. Comparison of the performances of different interfaces.

analyzed using a design tool to discern the factors that allow a mouse to perform better than other interfaces. The result of such an analysis will enable the development of new assistive computer interfaces with high efficiency. The developed interface methodology can be extended to control various platforms such as bionic robot systems for people with limb disabilities (i.e., disabilities involving exoskeletons and limb prostheses) and teleoperated robotic systems that can perform human tasks in hazardous environments.

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Human-robot interaction (HRI) is the study of interactions between people (users) and robots. HRI is multidisciplinary with contributions from the fields of human-computer interaction, artificial intelligence, robotics, speech recognition, and social sciences (psychology, cognitive science, anthropology, and human factors). There has been a great deal of work done in the area of human-robot interaction to understand how a human interacts with a computer. However, there has been very little work done in understanding how people interact with robots. For robots becoming our friends, these studies will be required more and more.

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