A Biosignal-Based Human Interface Controlling a Power-Wheelchair for People with Motor Disabilities

Ki-Hong Kim, Hong Kee Kim, Jong-Sung Kim, Wookho Son, and Soo-Young Lee

ABSTRACT—An alternative human interface enabling people with severe motor disabilities to control an assistive system is presented. Since this interface relies on the biosignals originating from the contraction of muscles on the face during particular movements, even individuals with a paralyzed limb can use it with ease. For real-world application, a dedicated hardware module employing a general-purpose digital signal processor was implemented and its validity tested on an electrically powered wheelchair. Furthermore, an additional attempt to reduce error rates to a minimum for stable operation was also made based on the entropy information inherent in the signals during the classification phase. In the experiments, most of the five participating subjects could control the target system at their own will, and thus it is found that the proposed interface can be considered a potential alternative for the interaction of the severely disabled with electronic systems.

Keywords—Human-Computer Interface, EEG, EMG.

I. Introduction

As a result of a variety of accidents or diseases such as a spinal cord injury (SCI) or amyotrophic lateral sclerosis (ALS), many people suffer from a severe loss of motor function. These people are forced to accept a reduced quality of life, depending on the care of other individuals. Even though useful human-computer interfaces based on speech or biometrics have been developed to communicate with computers, most of them are aimed at providing people without disabilities with more convenient or advanced means, while neglecting individuals with severe disabilities. Thus, the needs for a novel interface to help the disabled lead a more improved life have been addressed, and corresponding effort has also been made in the fields related to rehabilitation engineering and user interface (UI) development.

One attempt attracting considerable attention in those fields involves the utilization of biosignals such as an electroencephalogram (EEG) or electromyogram (EMG) obtainable from the human body as a means for interaction with the surrounding world. In the field of brain-computer interface (BCI), meaningful information derived directly from a user's brain activity has been used to manipulate systems. However, despite the definite advantage unique to EEG signals that allows a system to be controlled only by one's thoughts, the poor signal-to-noise ratios in the spontaneous EEG signals and the lack of consistency in the signal patterns still make their application impractical. Compared to such drawbacks of EEG signals, EMG signals have more possibility to be applied to a wide range of users due to their easy controllability and insensitiveness to noises [1]. In this letter, a special interface based on these EMG signals that runs in a stand-alone mode is proposed, and its usefulness as a communication channel is investigated through a practical test on an electrically powered wheelchair, called a power-wheelchair throughout this letter.

II. Methods and Materials

1. Signal Acquisition

The optimal electrode positions for the signal under consideration are sought out on the face, because the target users of the proposed interface are people paralyzed below the neck. Once several electrodes are attached to the appropriate positions around the forehead, cheeks, and eyes, a subject was instructed to make particular movements or actions predefined for signal acquisition, in which clenching of the teeth, blinking

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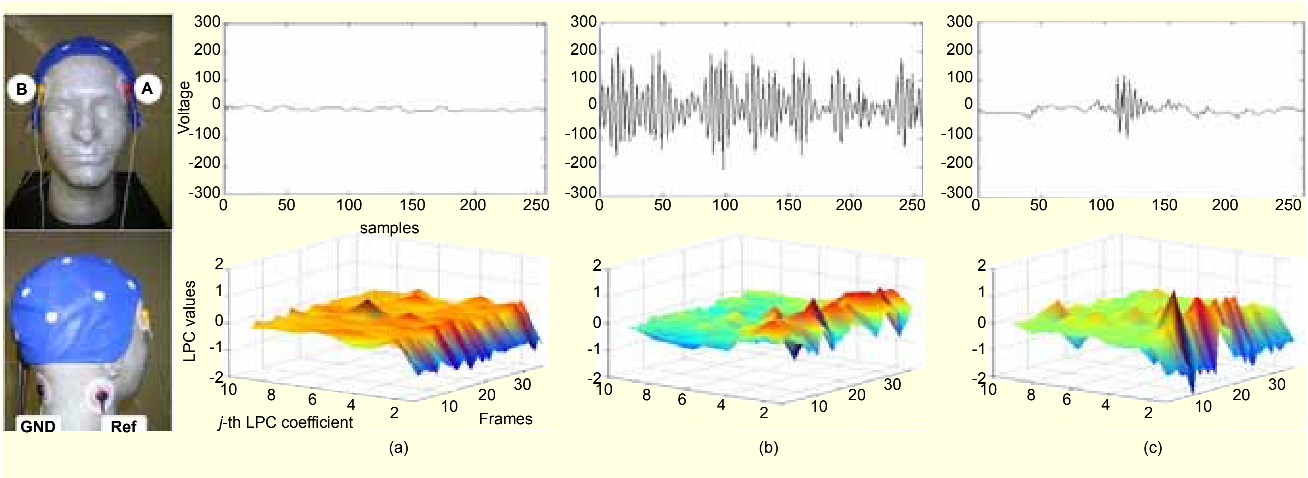

Fig. 1. The electrode positions, signals, and LPC patterns caused by predefined actions such as (a) no physical movement, (b) clenching left molar teeth, or (c) blinking both eyes. All signals are measured from the electrode attached to the left temporalis muscle (Ⓐ). X axis: 256 samples, 0.5 s long, Y axis: arbitrary voltage units.

of the eyes, wrinkling the forehead, and frowning are included. During such experiment, the positions of the electrodes chosen initially are fine-tuned gradually to be more appropriate by checking if some striking signal pattern specific to each action can be observed through a measuring instrument. Through many trials and errors, it was found that the contraction of temporalis muscles around the edge of each eye, while the subject clenched his or her teeth or blinked his or her eyes, produced a few distinguishable signals. Figure 1 shows the positions of the four electrodes and signal patterns caused by the actions mentioned.

The subjects participating in the experiment consist of five disabled individuals (two females and three males) ranging from 25 to 52 years in age. All the subjects have a severe loss of motor function caused by traffic or hiking accidents.

2. Analysis of Signals

Linear prediction coefficients (LPCs) and LPC entropy were adopted as features representing characteristic information contained in the measured signal. An LPC, which can be expressed as the coefficient a_j in (1), is employed often to approximate a sample value at a certain time with several sample values preceding it in time aspect, reducing the error e_n between the original signal s_n and the estimated signal $\tilde{s}_n$ to a minimum. The LPC order $p = 9$ was chosen based on the conclusions drawn from a brute force algorithm.

$$\tilde{s}_n = \sum_{j=1}^{p} a_j s_{n-j}, \quad p = 9$$

$$e_n = s_n - \tilde{s}_n = s_n - \sum_{j=1}^{p} a_j s_{n-j} \tag{1}$$

$$E = \sum_{n=1}^{N} e_n^2 = \sum_{n=1}^{N} \left(s_n - \sum_{j=1}^{p} a_j s_{n-j} \right)^2$$

For estimating time-varying LPC parameters, a signal of 0.5 s, sampled at a rate of 512 Hz, is first divided into short segments, generally called frames, and LPCs are then extracted from each frame. The feature vector set obtained in this way represents a time course of the LPCs that describes the time-varying characteristics of the signal. A time of 30 to 50 ms was used as the frame length, and the overlap rate of frames was 50%. Figure 1 shows how the LPC parameters extracted from each frame change as time passes. As in the figure, there are distinct differences among the three patterns of the LPC parameters.

3. Pattern Classification

A hidden Markov model (HMM) comprising three states and two Gaussian mixtures per state was employed as the classifier because it has been found suitable to model the dynamic changes of a certain complex signal, overcoming the problem of nonstationarity. Classification is done by comparing the likelihood values for an arbitrary feature sequence evaluated from four HMMs, HMM_L, HMM_R, HMM_F, and HMM_B for left, right, forward, and backward, respectively, and selecting the model with the maximum value. In this case, the likelihood value for the sequence $\mathbf{O} = [O_1, O_2, ..., O_T]$ given the HMMs can be expressed as $P(\mathbf{O}|\mathrm{HMM}_{L/R/F/B})$. The overall correct classification rate occurring in the five subjects mentioned in section II.1 was around 97.2%. However, to use the classification results as commands to control a power-wheelchair for the physically disabled, an improvement in success rate is strongly required.

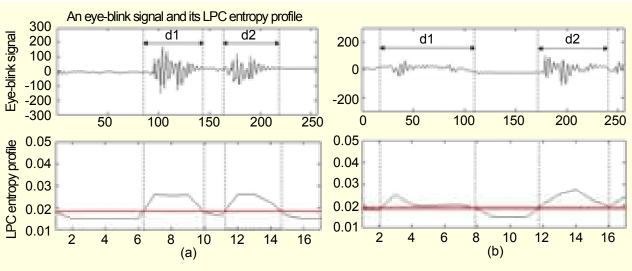

Fig. 2. Signal patterns and their LPC entropy profiles of (a) an eye-blink and (b) noise.

Table 1. Confusion matrix showing the classification rates (%).

Actions (clench or blink)	Class	HMMs ($HMM_{L/R/F/B}$)			
		L	R	F	B
Left teeth	L	98.2			1.8
Right teeth	R	2.2	97.8		
Both eyes	F	2.6	1.4	93.5	2.5
Both teeth	B	0.5	0.3		99.2
-	N	10.7	8.5	78.6	2.2

After many experiments, we found most error cases happened when unconscious head movement added noises on an incoming signal. These noises were a little similar to eye-blink signals in shape and thus were frequently mistaken for them in the classification phase. Figures 2(a) and 2(b) show an eye-blink (in this case, the eyes blinked twice) and a typical noise signal that frequently occurs. Table 1 describes the brief classification results from the disabled individuals.

In Table 1, L/R/B, F, and N signify the signals recorded while clenching the left/right/both sides of the subject's teeth, blinking both eyes, and the noise caused by a slight head movement, respectively. As shown in the table, most misclassifications were caused by the confusion of head movement with the eye-blinks.

The data set used for the subject-dependent classification consists of 4800 data for training (240 data for each class per subject) and 7000 data for testing (350 data for each class per subject). To tackle the previously mentioned confusion problem effectively, we prepared the additional criterion necessary for a final decision on whether or not the pattern identified is a true eye-blink. That criterion was set based on information about the boundaries detected using the LPC entropy feature.

4. Boundary Detection by LPC Entropy Profile

A signal picked up while a subject blinks his/her eyes looks like a kind of burst with short duration. Judging from the fact that eye-blinks are characterized mainly by such bursts, and thus apparently discriminated from the ones obtained by clenching of the teeth, whether or not there exists a burst in the incoming signal gives a decisive clue to the correct identification. In a real-world case, however, such a distinct classification can rarely be expected because various noises generated by unconscious head movement also have a few burst components in them, and these are mistaken for eye-blinks too often. Fortunately, we found after analyzing the signals, that noises arising spontaneously generally have bursts with longer durations as compared to those of eye-blinks. And in many cases, the number of bursts is more than two. Therefore, an exact detection of the starting and ending points of a burst signal, namely the boundaries, must be needed for higher recognition rates. Figure 2 depicts two signals that are quite different from each other in terms of features characterizing a burst, such as the duration and number of bursts.

To find these features, we used LPC entropy information as the key factor for boundary detection [2], [3]. This algorithm is carried out on the LPCs extracted to train HMMs in an earlier stage. First, the probability distribution for each LPC coefficient is determined within each frame. The LPC entropy for each frame is then computed as

$$H_n = -\frac{1}{K}\sum_{j=1}^{K} p_{nj}\log_2 p_{nj}, \qquad p_{nj} = |a(n,j)|^2 \Big/ \sum_{n=1}^{N} |a(n,j)|^2, \tag{2}$$

where $a(n,j)$ means the j-th LPC coefficient of the n-th frame and K is the LPC order. Assuming the number of total frames in the signal is N, the following LPC entropy profile ρ can be obtained:

$$\rho = [H_1 H_2, \ldots, H_N]. \tag{3}$$

Second, based on this LPC entropy profile, an appropriate threshold Γ is chosen for determining the existence of a burst within the acquired signal. The formula for finding the threshold is expressed in (4), and the value α is determined by trial-and-error. In our case, 0.95 is adopted as an optimal value.

$$\Gamma = \frac{\max(\rho) - \min(\rho)}{2} + \alpha \min(\rho), \qquad \max(\rho) = \max\left(H_i \middle| H_i \in \rho,\ 1 \le i \le N\right). \tag{4}$$

Once a threshold is determined, the part over the threshold is considered to be a burst, and all the other parts correspond to either silence or noise. The boundaries of a burst found by this end-point detection algorithm are represented as dotted lines in Fig. 2. Without such additional processing, the noise signal in Fig. 2(b) might be classified as an eye-blink, as shown in Fig. 2(a), in terms of the likelihood value evaluated in each HMM in the

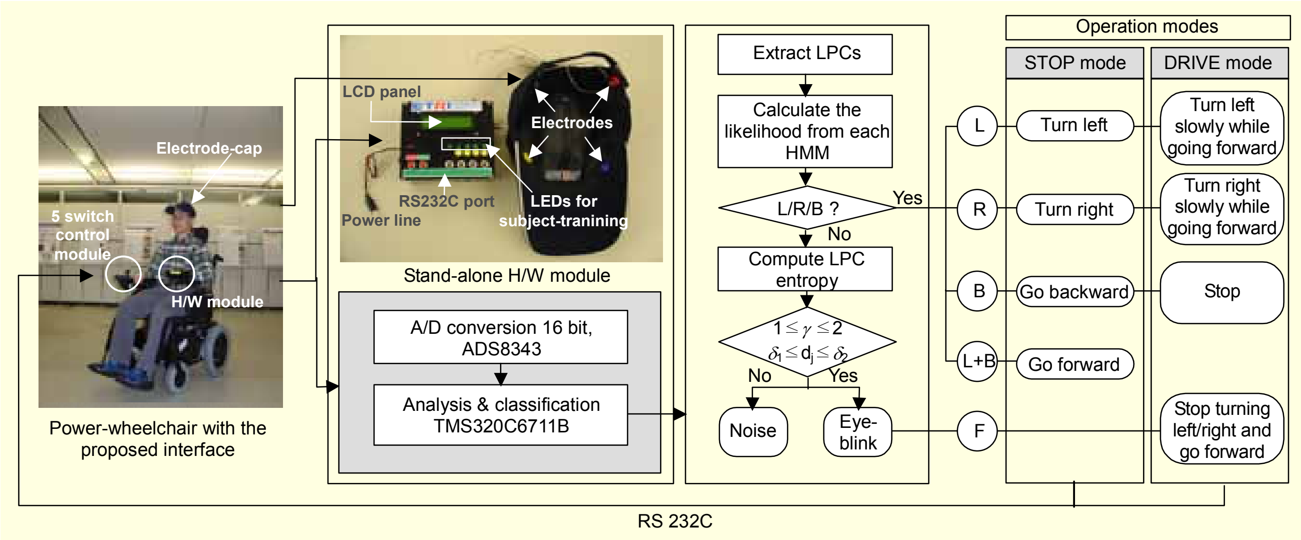

Fig. 3. The appearance of the developed interface system and a flow chart showing the entire operation of a power-wheelchair.

classification phase. The criteria on two factors, namely the duration and number of bursts, are as follows:

$$S_i = \begin{cases} S_e & \text{if } 1 \le \gamma \le 2, \quad \delta_1 \le d_j \le \delta_2, \quad j = 1,2, \\ S_n & \text{otherwise}, \end{cases} \tag{5}$$

where S_i, S_e, S_n represent an incoming signal, an eye-blink, and the noise signal, respectively, and γ, d_j, δ_1, δ_2 indicate the number of bursts, the duration of each burst, and the lower and upper limits of the duration, respectively. Here, δ_1 and δ_2 were determined by averaging the durations of all the bursts found in the training data. Through the aforementioned entropy information, we could attain a much better classification rate, which amounts to about 99.1%.

III. The Control of a Power-Wheelchair

For practical application, a stand-alone interface system employing a general-purpose digital signal processor (DSP) (TMS320-C6711B) was implemented and its validity was tested on a power-wheelchair. The size of this system is 12 × 11 × 5.5 cm, and the control commands decoded in the DSP, which are associated with particular directions such as left, right, forward, or backward, are transferred to the 5-switch module (manufactured by Dynamic Controls, New Zealand) of the power-wheelchair via the RS232C port. The control of a power-wheelchair by the proposed interface is done for two modes, STOP and DRIVE modes. As might be understood easily, if a wheelchair in STOP mode begins to move, its status changes into DRIVE mode and stays in that mode until the wheelchair stops. Figure 3 shows the appearance of the developed interface and a flow chart illustrating the entire operation of the power-wheelchair in more detail. In the figure, Ⓛ, Ⓡ, Ⓑ, and Ⓕ indicate the classified results for actions a subject made to generate control commands during each operation mode. According to the rules defined, the subject can make the wheelchair turn left slowly while going straight by clenching the left molar teeth, and stop it by clenching both left and right molar teeth for a short time.

IV. Conclusion

An alternative interface introduced in this letter enables many severely disabled people to control an assistive system for themselves, relying on the biosignals captured while contracting muscles on their face. From the performance test of the interface for the disabled in the *National Rehabilitation Center* in Korea, it was discovered that all the participants could drive a power-wheelchair in every direction they wanted within about 40 minutes. Although an approach to adopt LPC parameters and an LPC entropy profile as features was found effective, if the combination of available actions is also allowed to make another command, more elaborate operation of a power-wheelchair may be possible, reducing error rates more significantly.

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