International Conference on Control, Automation and Systems 2010
Oct. 27-30, 2010 in KINTEX, Gyeonggi-do, Korea

Non-invasive brain signal interface for a wheelchair navigation

Bong-Gun Shin[1], Taesoo Kim[2] and Sungho Jo[1]

[1]Department of Computer Science, KAIST, Daejeon, South Korea
(Tel : +82-42-350-7740; E-mail: {bgshin, shjo}@kaist.ac.kr)
[2]Department of Electrical Engineering and Computer Science, MIT, Massachusetts, USA
(E-mail: taesoo@mit.edu)

Abstract: This work presents that, only using non-invasively captured brain signals, a person can navigate an electric wheelchair with no serious training for a long term. Only two electrodes are set on the scalp non-invasively to detect a P300 EEG signal and a reference signal. A simple signal processing interprets the measured signals to decide a movement direction of the wheelchair. The whole devices are loaded on the wheelchair. No external system is required. The experimental results demonstrate the feasibility of the simple BCI processing to achieve reasonable performance.

Keywords: Brain-machine interface, EEG, P300, wheelchair control

1. INTRODUCTION

BRAIN computer interface (BCI) has become a highly recognized research area. Especially, non-invasive approaches to monitor brain activity are of main interest to researchers due to its attractiveness on practical applications. It is not really new to use EEG signals for BCI. Researchers have developed technologies to use EEG as human commands to machines much as mobile robots [1], wheelchair [2] and a humanoid robot [3]. Especially, navigating a wheelchair using brain signal communication is challenging and risky because a human should sit on it and continuously keep monitoring the wheelchair's behavior. Simple communication process not required any pre-training or learning period will facilitate its navigation. Some results have been reported about the brain-based control of a wheelchair. Some investigators controlled a wheelchair only using EEG signals [2]. However, they required many trials for pattern generation and the EEG measuring system was not boarded on the wheelchair. In Craig and Nguyen's work [4], EEG signal classification provided three commands to the wheelchair with five commands by head movements. Their work also required training for classification. In another case, 64 channels were used to apply spatial filtering to select three steering commands [5]. A study demonstrated a possibility that a tetraplegic controls a wheelchair using EEG signals, however, it was tested only in virtual reality [6]. A P300 EEG based-BCI application to wheelchair control was investigated recently [7]. P300 signal is an event-related response, a positive potential peak evoked about 300ms after a visual stimulus is recognized. They used the brain signal to select a destination item on the menu not steering commands. Then, a wheelchair navigates along a predefined path. Therefore, this method requires preprogramming of all guiding paths in a given environment. P300-based BCI approach is generally advantageous because no serious user training is required. Another study about P300-based BCI to a wheelchair is reported [8]. P300 signals from multi-channels are recorded to decide a steering direction. They design a classification method based on a Bayesian approach. This work aims the development of a simple BCI approach to the control of a wheelchair using minimal EEG information and simple signal processing neither requiring significant training nor adaptive algorithms.

This work was supported by the Korea government (MKE) under Human Resources Development Program for Convergence Robot Specialists.

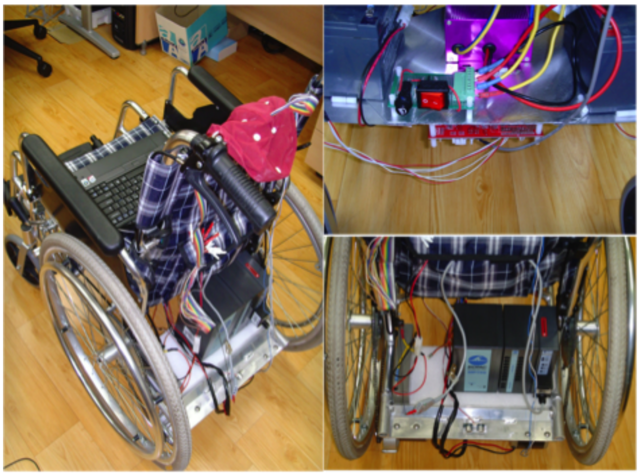


Fig. 1 The wheelchair system setup

2. METHOD

2.1 Wheelchair Design

An electric wheelchair (Fig. 1) was constructed by adding two 24V 200W 300RPM DC motors to a commercial wheelchair. Torque generated by each motor is transmitted to each main wheel through chains. Two parallel 12V lead-acid batteries supply powers. Ultrasonic distance sensors are attached on every side of the wheelchair to provide anti-collision system. A laptop computer communicates with the motor controller through USB serial. We use two communication channels, one for controlling two motors (PWM control), and the other for communicating with the ultrasonic sensors. The laptop computer is also used for EEG data acquisition and processing. The computer's operation is under an Intel Core2 Duo @ 2 GHz running Windows OS. The ultrasonic sensors detect distance information in a real-time. Atmega-128 board buffers the sensed information and send it to the computer where situation recognition algorithm is run. The recognition algorithm reads distance information every 30ms. If sensed distance from any among four sensors is less than 30m, motor operation stops promptly. This system is designed for safe navigation during tests. Hand-brake system is also equipped to protect from urgent situations.

2.1.1 EEG data acquisition and processing

To detect the EEG signals, we use the Biopac MP150 EEG system which consists of an electrode attached a cap, signal amplifier, an electrode box, an analog-to-digital (A/D) converter. The EEG system is connected to the laptop computer mentioned previously. An electrode is located on the scalp of a subject to detect the P300 visually evoked potential. The reference electrode is placed on the earlobe. The EEG signal is recorded at sampling rate of 1kHz. To avoid artifacts during EEG recording, we used a bandpass filter of 1-35Hz. Artifact removal by filtering is not perfect so that a subject is asked to minimize the movements of his or her body and eyes during operation. The EEG system with its padded bottom is loaded on the wheelchair. The EEG system uses a separated power supply from motors to reduce noise signals. The detected EEG signals are sent to the computer via 10Mbps Ethernet.

2.1.2 BCI system setup

We use P300 signal as BCI command to indicate the movement direction of the wheelchair in real time. To enable to do so, we first had to evaluate and calibrate the P300 signal acquisition and processing protocols off-line. The off-line signal acquisition experiment is implemented as follows. A subject sits at desk wearing a cap equipped with electrodes and connected to the EEG detection system. EEG signals are recorded from 16 electrode channels placed on the scalp according to standard electrode system [????]. In experiment, the subject watches commands quickly flashing at the center of a computer monitor. Four possible commands {Left. Right, Forward, Backward} flash. The commands flicker every 200ms in a random sequence. P300 peaks would evoke whenever the subject detects expected commands visually. While commands other than the expected pop up, no P300 signal appearance is expected. The P300 signal detection is operated in the interval of 250ms after each command disappears. A P300 signal is detected in about 100ms if it really exists because the flash lasts 200ms. To detect P300 signals, we come up with two approaches. First, we test the support vector machine (SVM). Using an open resource [9], the best performing classifier to distinguish existence and nonexistence of P300 signal is automatically determined based on experimental data. However, this approach cannot predict if a P300-like signal is really evoked due to proper visual stimuli or any other artifacts. This method works well

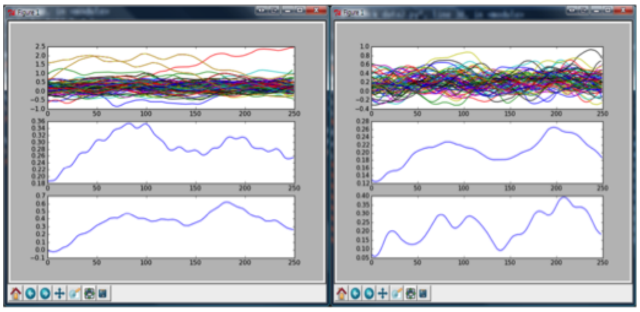


Fig. 2 Recorded P300 signal profiles

in static condition, but not much while a person moves on a wheelchair so that undesired possible noises can affect brain signals. Next, we suggest averaging brain signal profile samples. From recording section, all potential P300-like signal profiles in every 250ms after correct commands flash are averaged. Averaging out mediates the noise effect. On the other hands, expected profiles of non P300 signals every after wrong commands flash are also averaged. Throughout the off-line experiment, we concluded an electrode channel is express enough to command. This is good regarding the convenience and simplicity of the interface device design. Also, the placement of the channel is chosen to be Parietal Cortex (Pz), where P300 signal is well detected.

2.1.3 Motion execution protocol

Real time detection of P300 signal requires a different protocol from batch detection. We use the averaging method mentioned previously. Before navigation begins, Off-line EEG recording is implemented for 2 minutes. Using the data obtained in this period, we compute averaged profile of P300 signals in the interval of 250ms, which is to be a basis profile of P300 signal. Once navigation begins, a subject tries to detect a desired command fixating attention to 10 flashing commands every 200ms. Among 10 flashes, the desired command exists at least one time. Detected P300-like signal profiles responding the desired commands are averaged out. Brain signal profiles for other corresponding commands are also respectively averaged out. The whole averaged profiles have the duration of 250ms. Then, each averaged profile is compared with the basis profile obtained before execution. By calculating the root mean square (RMS) of two profiles, the basis and an averaged profile corresponding to each command, a command is selected. An average profile of which corresponding RMS value is smallest is most likely to be a P300 signal profile. Therefore, the wheelchair executes according to the corresponding command. The reason of averaging signals is to attenuate any artifacts.

3. EXPERIMENT

To evaluate the application of the proposed algorithm to the wheelchair navigation, we conduct experiments. A person sits on the designed wheelchair and spends about

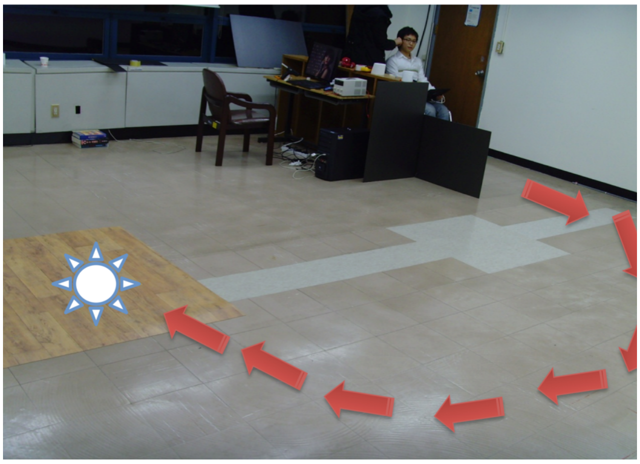
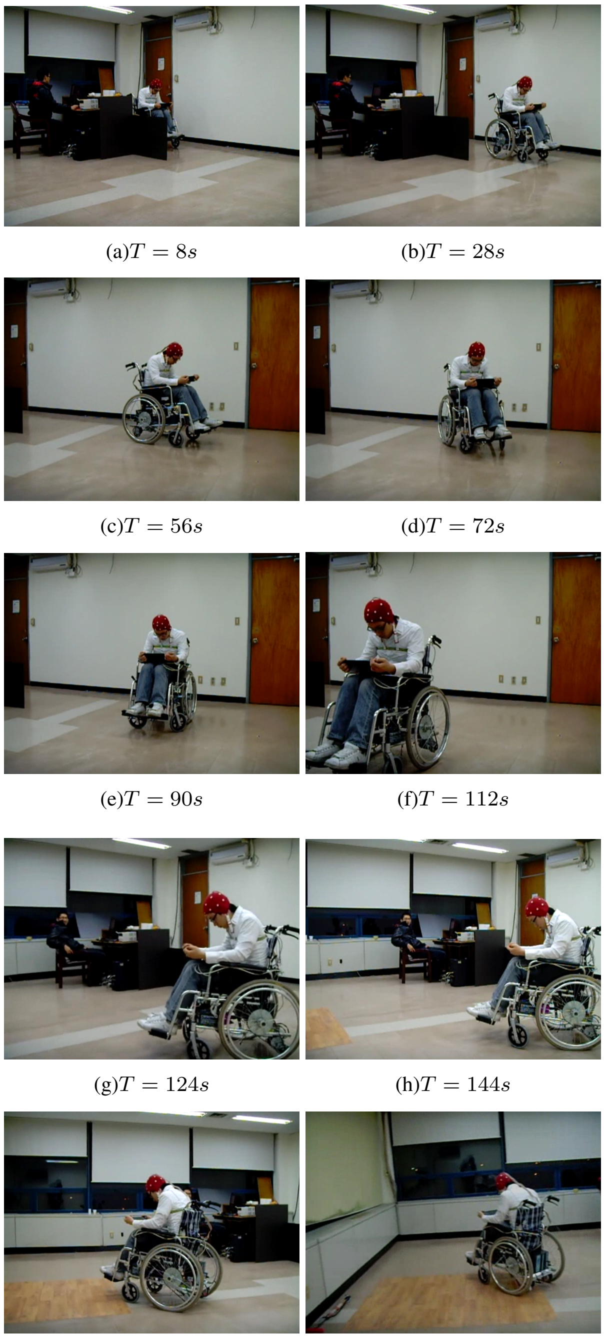


Fig. 3 Desired path trajectory

2 minutes to do training. Detected P300 signals during the training are used to set a basic profile of P300 for the specific person. In the experiment, the person is asked to control the wheelchair to a destination position as in Fig. 3. The subject was able to drive the wheelchair along the desired trajectory using only brain signals. The trajectory is roughly 8 meters long and it took about 170 seconds for the subject to make the wheelchair follow the trajectory. The system runs with two separate phases. At the first phase, user's P300 signal is analyzed to recognize the intended command. After the first phase, the wheelchair is operated according to the recognized command. Hence there are some delays in between two consecutive commands. Each picture in the Fig. 4 shows the execution of each command.

4. DISCUSSION

We present the wheelchair navigation system successfully using non-invasively captured brain signals. The system is capable of navigating the desired trajectory with just a few number of electrodes. While the wheelchair is moving, lots of noises from the power unit of motors keep the P300 classifier from distinguishing desired commands. Even the wheelchair is not moving, sometimes the EEG signals are disturbed by some noise. To attenuate this undesired phenomena, the EEG system uses a separated power supply from motors to reduce noise signals. and the system was designed to have two separate phases. For the same reason, we repeat the P300 detection procedure for several times to get reliable result. We can get the robust system, but the undesirable repetition causes the system delay. The average delay caused by choosing a command is about 20s. Minimizing the delay would be a good research topic for the future work. The simultaneous structure where the system recognize a command while it executes the previous one, can be realized using appropriate noise modeling and filtering methods.



(a)$T = 8s$ (b)$T = 28s$

(c)$T = 56s$ (d)$T = 72s$

(e)$T = 90s$ (f)$T = 112s$

(g)$T = 124s$ (h)$T = 144s$

(i)$T = 144s$ (j)$T = 168s$

Fig. 4 Experiment result

REFERENCES

[1] J. Millán, F. Renkens, J. Mouriño, and W. Gerstner, "Noninvasive brain-actuated control of a mobile robot by human EEG," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 1026–1033, 2004.

[2] K. Tanaka, K. Matsunaga, and H. Wang, "Electroencephalogram-based control of an electric wheelchair," *IEEE Transactions on Robotics*, vol. 21, no. 4, pp. 762–766, 2005.

[3] C. Bell, P. Shenoy, R. Chalodhorn, and R. Rao, "Control of a humanoid robot by a noninvasive brain-

computer interface in humans," *J. Neural Eng*, vol. 5, no. 2, pp. 214–220, 2008.

[4] D. Craig and H. Nguyen, "Adaptive EEG thought pattern classifier for advanced wheelchair control." in *Conference proceedings:... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, vol. 2007, 2007, p. 2544.

[5] F. Galán, M. Nuttin, D. Vanhooydonck, E. Lew, P. Ferrez, J. Philips, and J. Millán, "Continuous brain-actuated control of an intelligent wheelchair by human EEG," in *Proceedings of the 4th International Brain-Computer Interface Workshop and Training Course, TU Graz/B
"uroservice, Graz*, 2008, pp. 315–320.

[6] R. Leeb, D. Friedman, G. Muller-Putz, R. Scherer, M. Slater, and G. Pfurtscheller, "Self-Paced(Asynchronous) BCI Control of a Wheelchair in Virtual Environments: A Case Study with a Tetraplegic," *Computational Intelligence and Neuroscience*, vol. 2007, p. 79642, 2007.

[7] I. Iturrate, J. Antelis, A. K
"ubler, and J. Minguez, "Non-invasive brain-actuated wheelchair based on a p300 neurophysiological protocol and automated navigation," *IEEE Transactions on Robotics*, vol. 25, no. 3, pp. 614–627, 2009.

[8] G. Pires, M. Castelo-Branco, and U. Nunes, "Visual P300-based BCI to steer a wheelchair: A Bayesian approach," in *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, 2008, pp. 658–661.

[9] C.-C. Chang and C.-J. Lin, *LIBSVM: a library for support vector machines*, 2001, software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm.