Clinical Neurophysiology 119 (2008) 2159–2169

www.elsevier.com/locate/clinph

A brain-actuated wheelchair: Asynchronous and non-invasive Brain–computer interfaces for continuous control of robots

F. Galán[a,b,*], M. Nuttin[c], E. Lew[a], P.W. Ferrez[a], G. Vanacker[c], J. Philips[c], J. del R. Millán[a,d,*]

[a] IDIAP Research Institute, Centre du Parc., Av. des Prés-Beudin 20, CH-1920 Martigny, Switzerland
[b] University of Barcelona, Barcelona, Spain
[c] Department of Mechanical Engineering, Katholieke Universiteit Leuven, Leuven, Belgium
[d] Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland

Accepted 2 June 2008

Abstract

Objective: To assess the feasibility and robustness of an asynchronous and non-invasive EEG-based Brain–Computer Interface (BCI) for continuous mental control of a wheelchair.
Methods: In experiment 1 two subjects were asked to mentally drive both a real and a simulated wheelchair from a starting point to a goal along a pre-specified path. Here we only report experiments with the simulated wheelchair for which we have extensive data in a complex environment that allows a sound analysis. Each subject participated in five experimental sessions, each consisting of 10 trials. The time elapsed between two consecutive experimental sessions was variable (from 1 h to 2 months) to assess the system robustness over time. The pre-specified path was divided into seven stretches to assess the system robustness in different contexts. To further assess the performance of the brain-actuated wheelchair, subject 1 participated in a second experiment consisting of 10 trials where he was asked to drive the simulated wheelchair following 10 different complex and random paths never tried before.
Results: In experiment 1 the two subjects were able to reach 100% (subject 1) and 80% (subject 2) of the final goals along the pre-specified trajectory in their best sessions. Different performances were obtained over time and path stretches, what indicates that performance is time and context dependent. In experiment 2, subject 1 was able to reach the final goal in 80% of the trials.
Conclusions: The results show that subjects can rapidly master our asynchronous EEG-based BCI to control a wheelchair. Also, they can autonomously operate the BCI over long periods of time without the need for adaptive algorithms externally tuned by a human operator to minimize the impact of EEG non-stationarities. This is possible because of two key components: first, the inclusion of a shared control system between the BCI system and the intelligent simulated wheelchair; second, the selection of stable user-specific EEG features that maximize the separability between the mental tasks.
Significance: These results show the feasibility of continuously controlling complex robotics devices using an asynchronous and non-invasive BCI.

Keywords: Brain–computer interfaces; Electroencephalogram (EEG); Asynchronous protocol; Feature selection; Intelligent wheelchair; Shared control

1. Introduction

The possibility to act upon the surrounding environment without using our human nervous system's efferent pathways enables a new interaction modality that can boost and speed up the human sensor–effector loop. In recent years, brain–computer interface (BCI) research is exploring many applications in different fields: communication, environmental control, robotics and mobility, and neuroprosthetics (Birbaumer et al., 1999; Obermaier et al., 2003; Bayliss, 2003; Millán, 2003; Nicolelis and Chapin, 2002; Millán et al., 2004; Carmena et al., 2003). Our work in

* Corresponding authors. Address: IDIAP Research Institute, Centre du Parc., Av. des Prés-Beudin 20, CH-1920 Martigny, Switzerland. Tel.: +41 277217770; fax: +41 277217712.

E-mail addresses: ferran.galan@idiap.ch (F. Galán), jose.millan@idiap.ch (J. del R. Millán).

1388-2457/$34.00
doi:10.1016/j.clinph.2008.06.001

the MAIA project[1] aims at developing asynchronous and non-invasive BCI to control robots and wheelchairs (Millán et al., 2004; Lew et al., 2006). It means that users control such devices spontaneously and at their own paced, by learning to voluntarily control specific electroencephalogram (EEG) features measured from the scalp. To this end, users learn how to voluntarily modulate different oscillatory rhythms by the execution of different mental tasks (motor and cognitive). To facilitate this learning process, we rely upon machine learning techniques, both to find those subject-specific EEG features that maximize the separability between the patterns generated by executing the mental tasks (Galán et al., 2007), and to train classifiers that minimize the classification error rates of these subject-specific patterns (Millán et al., 2004). Finally, to assist the control task, different levels of intelligence are implemented in the device jointly with shared control techniques between the two interacting agents, the BCI system and the intelligent device (Philips et al., 2007; Vanacker et al., 2007).

One of the main challenges of a non-invasive BCI based on spontaneous brain activity is the non-stationary nature of the EEG signals. Shenoy and co-workers (Shenoy et al., 2006) describe two sources of non-stationarity, namely differences between samples extracted from calibration measurements (training data set) and samples extracted during the online operation of the BCI system (test data set), and changes in the user's brain processes during the online operation (e.g., due to fatigue, change of task involvement, etc). Such kinds of phenomena have motivated the BCI research groups to develop adaptive algorithms to deal with these shifts in the distributions of samples (Shenoy et al., 2006; Buttfield et al., 2006; Vidaurre et al., 2006; Millán et al., 2007). Unfortunately, current adaptive solutions have two main limitations. Firstly, they are based on supervised approaches requiring the correct output for every sample, and so the user cannot operate the BCI autonomously. Secondly, adaptation in the wrong moment (e.g., when the user is not properly executing the mental tasks because of fatigue, distraction, etc) will incorrectly change the feedback (the device's behavior) and will disrupt user's learning process. Given this scenario, two questions arise. Is it possible to find (rather) stable subject-specific EEG features to reduce the differences between samples extracted from calibration and online operation sessions? How shared control techniques can minimize the impact of changes in the user's EEG signals during the online operation?

In this paper we describe an asynchronous brain-actuated wheelchair that can be operated autonomously, and report results obtained by two subjects while continuously driving a simulated version of the wheelchair. Our brain-actuated wheelchair exhibits two key components, namely the selection of stable user-specific EEG features that maximize the separability between the different mental tasks, and the implementation of a shared control system (Philips et al., 2007; Vanacker et al., 2007) between the BCI and the intelligent simulated wheelchair.

2. Methods

2.1. EEG data acquisition and preprocessing

EEG Data were recorded from two healthy subjects with a portable Biosemi acquisition system using 64 channels sampled at 512 Hz and high-pass filtered at 1 Hz. Then, the signal was spatially filtered using a common average reference (CAR) before estimating the power spectral density (PSD) in the band 8–48 Hz with 2-Hz resolution over the last 1 s. The PSD was estimated every 62.5 ms (i.e., 16 times per second) using the Welch method with five overlapped (25%) Hanning windows of 500 ms. Thus, an EEG sample is a 1344-dimensional vector (64 channels $\times$ 21 frequency components). Obviously, not all these 1344 features are used as control signals. Sections 2.2 and 2.3 describe the algorithms to estimate the relevance of the features for discriminating the mental commands and the procedure to select the most stable discriminant features that will be fed to the classifier embedded in the BCI. This classifier processes each of the EEG samples and the BCI combines eight consecutive responses to deliver a mental command every 0.5 s.

2.2. Calibration Sessions and Feature Extraction

To extract stable discriminant EEG features (see Section 2.3.2) and build the statistical Gaussian classifier embedded in the BCI (see Section 2.3.3), both subjects participated in 20 calibration sessions recorded in the same day as the test driving session 1. The calibration sessions were recorded during the morning and the test driving session 1 during the afternoon. As in the driving sessions, the subjects sat on a chair looking at a fixation point in the center of a monitor. The display was also the same, the simulated wheelchair being in a first person view (see Fig. 1, left). The subjects were instructed to execute the three mental tasks (left hand imagination movement, rest, and words association),[2] tasks utilized as mental commands to operate the wheelchair, in a self-paced way. The mental task to be executed was selected by the operator in order to counterbalance the order, while the subjects decided when they started to execute the mental task. Each calibration session was integrated by six trials each, two trials of each class. The duration of each trial was 7 s but only the last 6 s were utilized in the analysis to avoid preparation periods where

[1] *MAIA – Mental Augmentation through Determination of Intended Action*, http://www.maia-project.org.

[2] The mental tasks consisted in imagining repetitive self-paced movements of the left hand, getting relaxed centering attention on the fixation point placed on the center of the monitor, and searching words starting with the same letter.