Interacting with the Environment through Non-invasive Brain-Computer Interfaces

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Abstract. The brain computer interface (BCI) technology allows a direct connection between brain and computer without any muscular activity required, and thus it offers a unique opportunity to enhance and/or to restore communication and actions into external word in people with severe motor disability. Here, we present the framework of the current research progresses regarding non-invasive EEG-based BCI applications specifically devoted to interact with the environment. Despite of the technological advancement, the operability of a BCI device in an out-laboratory setting (i.e. real-life condition) still remains far from being settled. The BCI control is indeed, characterized by unusual properties, when compared to more traditional inputs (long delays, noise with varying structure, long-term drifts, event-related noise, and stress effects). Current approaches to this are constituted by post hoc processing the BCI signal in order to better conform to traditional control. A long-term approach is to devise novel interaction modalities. In this regard, BCI can offer an unusual and compelling testing ground for new interaction ideas in the Human Computer Interaction field.

Keywords: BCI, EEG, Applications, Functional Model, Standards.

1 Introduction

A Brain-Computer Interface (BCI) is a direct communication pathway between the user's brain and an external device [1, 2]. From a neurological point of view, BCIs bypass the user's peripheral nervous system (nerves) and his/her muscles, establishing a direct connection between the central nervous system (brain) and the environment the user operates in. In this interaction paradigm, it is not needed that the user contracts even a single muscle (e.g. to press a button, to vocalize his/her intent, or to direct his/her gaze), because the interface is able to recognize specific commands by recognizing his/her "brain states".

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The concept of direct pathway does not necessarily imply a physical contact with the brain. Many BCI devices have been proposed, which are based on non-invasive detection of correlates of brain functioning, such as bioelectromagnetic fields (exploited in electroencephalography- EEG- and Magnetoencephalography –MEG[3]) and concentration of metabolic products (exploited in Functional Magnetic Resonance Imaging – fMRI[4, 5] – and Near Infrared Spectroscopy – NIRS[6]). At present, practical considerations (such as cost and portability) only permit the use of EEG-based BCIs as viable interfaces for a real-life use.

In this paper, we will present the framework of the current research progresses regarding the field of non-invasive EEG-based BCI applications specifically devoted to interact with the environment. First, the neurological bases of the BCI control signals will be described with particular attention to event-related potential signals and the modulation of the sensorimotor rhythms; a second body of the paper will deal with the steps from the detection of BCI control signals to the translation of these electrophysiological signals into a semantic signals which is meaningful for the BCI interface application; as third issue we will introduce some applications of the BCI in terms of environmental interaction implemented in different related projects; finally, we will outline open questions related to the operability of a BCI device such as theoretical modeling and standardization whose ultimate goal is a formal introduction to a BCI general framework.

2 Neurological Principles

EEG-based BCIs rely on automated detection of the user's intent, based on the classification of patterns of his/her brain waves. The most successful approaches are the P300[7,8], steady-state visual evoked potentials (SSVEP)[9, 10] and oscillatory components based BCIs[11]. In all cases, the user has to interact with the system through an interface which functions as an online feedback to the users. However, whereas the oscillatory components based BCIs require the user to learn regulation of the target EEG response by means of the online feedback, in the event-related potential-based BCIs, an evoked brain potential is elicited by external stimuli and learning of voluntary brain regulation is not necessary (Fig.1).

The P300 event-related brain potential is a positive endogenous potential which occurs over the parietal scalp region when infrequent or particularly significant stimuli are interspersed with frequent or routine stimuli [12]. Because of its stability and reproducibility, the P300 has been proposed as a control signal for brain computer interface (BCI) systems [13]. The P300-based brain computer interface presents e.g. 36 characters on the screen that flashed up in a random order. The subject controlling the BCI has to look at the character he wants to spell. Whenever, the desired target character will flash up, the P300 component is produced in the brain and this reaction can be analyzed with parameter extraction and classification algorithms. The P300 concept has been the classical way to create a spelling device (see below; [8]). In the SSVEP based BCIs, the subject is presented with flashing lights that flicker with a specific frequency of e.g. 11, 12, 13 and 14 Hz. This interface presentation can generate, when the subject is looking at one of the lights, an EEG signal exactly at this frequencies and this will be detected with signal processing methods in the EEG raw data. Therefore a cursor movement (BCI application to train people) can be generated for instance, with 4 lights. Finally, in the BCI based on the EEG oscillatory components, selective EEG rhythm changes relevant to motor performances can be detected and function as control signal. In particular, in this type of interaction, the subject is confronted with a cursor moving on a screen and he/she has to learn to control the cursor movement toward a given target; the learning is based on a motor imagery task (e.g. a right-left hand/foot movement) that will induce an event-related desynchronization (ERD) of the motor–related EEG rhythms. Indeed, it is well known that sensorimotor rhythms (SMRs; in the alpha and lower beta EEG frequency ranges) decreases or desynchronizes with movement, preparation for movement or movement imagery and increases or synchronizes in the post-movement period [14]. This ERD can be again detected over the scalp motor regions, with dedicated parameters extraction and classification algorithms [15]. At the present state of the art, several BCI systems can be operated with all 3 EEG signals [1].

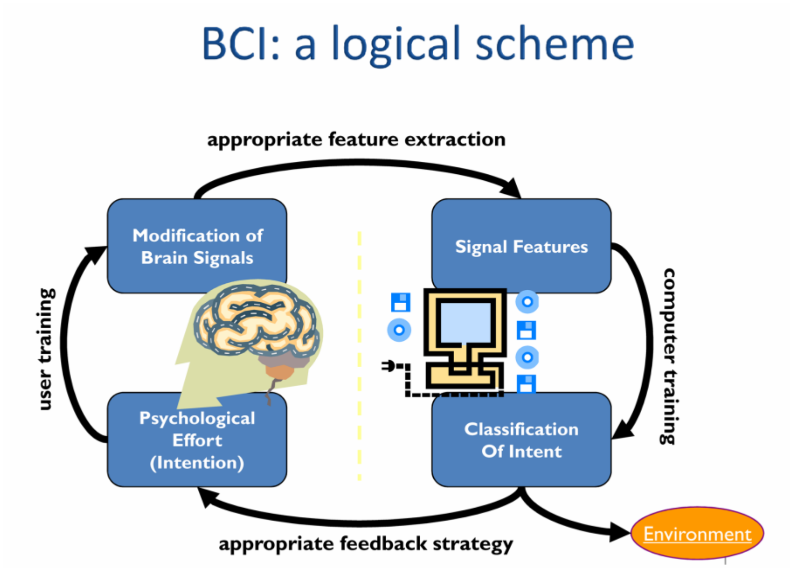

Fig. 1. The scheme illustrates the several conceptual steps fundamental to a classical EEG – based Brain Computer Interface (BCI) loop. The user's intent is expressed by means of different attentive-cognitive tasks (for instance, attention to a "desired" target or motor imagery); these tasks induced a modification of the brain electrical activity (EEG evoked potentials or EEG oscillatory components). The stability of this link is achieved during the user's training. Thus, some relevant features are extracted by the brain signals (EEG), classified and eventually translate into an action on the external world. What is crucial in this paradigm is the feedback to the user of her/his rain signal modulations which is instrumental for interacting via a BCI channel.

3 From Brain States to Control of Devices

The two main functional blocks of a BCI system are the Transducer and the Control Interface [16; 17], and four main steps are needed to convert brain states into control of devices, namely biosignal collection, extraction of relevant features, decoding of feature patterns, and translation into a control signal (Fig. 2).

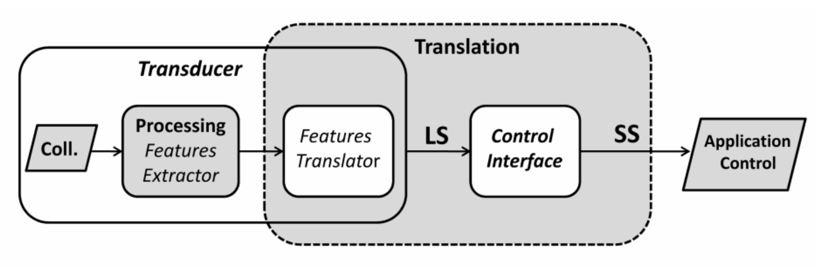

Fig. 2. Functional model of a BCI system

The Transducer deals with the collection of data, the extraction of the features of interest and the first step of translation. In the collection phase, bioelectrical signals are collected from the surface of the scalp using electrodes, whose number ranges from 2 (simple applications) to 128 (brain mapping studies). These signals, whose amplitude is just a few microvolts, are amplified, digitized and sent to a processor. In the processing phase, relevant features are extracted from biosignals (Features Extractor). Processing may consist in averaging over a few repetitions of the same response of the brain to an external stimulus (as in the case of BCIs based on P300, see below), or in the analysis of spectral properties of the electroencephalographic signal (as in the case of BCIs based on sensorimotor rhythms). Then, these features are combined (linearly or nonlinearly), by means of the Features Translator, into a logical signal. These logical signals can be mapped into logical symbols (LS) that may either be an analogical signal (e.g. a degree of displacement from baseline values), or a discrete output (e.g. an actual classification). LSs constitute the input to the Control Interface which, in the second step of the translation, converts them, by means of some encodings, into a semantic symbol (SS), which is meaningful for the application control interface (e.g., in the case of a computer application, how many pixels a cursor should be displaced, which command was selected in a menu, etc.).Semantic symbols are finally translated into physical controls for the actual application, which may consist of, for instance, a computer program, an assistive device, a robot, or a domotic environment [18].

4 Current BCI Applications

A non-exhaustive list of non-invasive BCI applications is given in the following. The aim is to provide a summary of current applications of BCI, and to form the base to discuss open issues. First, intuitive BCI application is communication and environmental control. Recently, non invasive EEG-based BCIs have gained interest as a control modality for robotic devices to increase mobility (like a wheelchair).

4.1 Support to Communication

In a classical BCI application to increase or even to allow communication, introduced by Farwell and Donchin in 1988 [19], the subject can “mentally” select letters from a screen to write sentences. In this type of interaction, based on P300 control signals, users are presented with a 6x6 matrix where each of the 36 cells contains a letter or a symbol. The paradigm design is such that each row and column is intensified for 100 ms in random order and then, by instructing participants to attend to only one (the desired) of the 36 cells. Thus, in one trial of 12 flashes (6 rows and 6 columns), the target-desired cell will flash only twice constituting a rare event, compared to the 10 flashes of all other rows and columns and will therefore elicit a P300 [8]. Although with the limit of a low rate of information transfer (about 2 letters per minute, [20]) this BCI application has been successful in allowing communication in persons who have lost control of their muscles but have cognitive function preserved (so called locked-in syndrome) [21]. The “mental” text entry application ‘Hex-o-Spell’ incorporates principles of Human-Computer Interaction research into BCI feedback design [22]. Indeed, here the focus is on the challenge in designing a “mental” typewriter: to map a small number of BCI control states (typically two) to the high number of symbols (26 letters plus punctuation marks) while accounting for the low signal to noise ratio in the control signal. The system utilizes the high visual display bandwidth to help compensate for the extremely limited control bandwidth which operates with only two mental states (usually motor imagery of right hand and right foot), where the timing of the state changes encodes most of the information. The display is visually appealing (a moving arrow), and control is robust [23]. One of the aims of Hex-o-Spell is to make the best use of the language model to reduce the effort required to enter text, without inducing enormous cognitive load or extensive training time. There are four common approaches to introducing language models into text entry systems: post hoc interpretation (e.g. as used in T9); adaptive target resizing (as in Dasher, [24]); dynamics adjustment (as in the original Hex); and layout re-ordering (used in Hex-o-Spell). The re-arrangement strategy does require visual search at every new letter input, but the minimal reorganization algorithm used in Hex-o-Spell significantly reduces the impact of this. Compared to other potential entry styles, such as Dasher or grid selection mechanisms, Hex-o-Spell is also very visually compact; the hexagonal display can potentially be used as a small overlay on top of a text being edited, giving the user an overview of the context in which they are editing.

4.2 Domotic Control

In this section, we will illustrate a pioneering introduction of the BCI technology into the principles of the assistive technology (AT) devoted to the people’s daily life interaction with the environment. This introduction was one the aims of a project named ASPICE (Italian Telethon Foundation, GUP03562), addressing the implementation and validation of a technological aid that allows people with motor disabilities to improve or recover their mobility and communicate within the surrounding environment [18]. The key elements of the system are: (1) Interfaces for easy access to a computer: mouse, joystick, eye tracker, voice recognition, and utilization of signals collected directly but non-invasively from the brain using an EEG-based BCI system. The rationale for the multiple access capacities was twofold: (i) to widen the range of users, but tailoring the system to the different degrees of patient disability; (ii) to track individual patient’s increase or decrease (because of training or reduction of abilities, respectively) to interact with the system, according to the residual muscular activity present at the given moment of the disease course and eventually to learn to control the system with different accesses (up to the BCI) because of the nature of neurodegenerative diseases which provoke a time progressive loss of strength in different muscular segments. (2) Controllers for intelligent motion devices that can follow complex paths based on a small set of commands. (3) Information transmission and domotics that establish the information flow between subjects and the appliances they are controlling. Implementation of the prototype system core took advantage of advice and daily interaction with the users. It was eventually realized as follows. The core unit received the logical signals from the input devices and converted them into commands that could be used to drive the output devices. Its operation was organized as a hierarchical structure of possible actions, whose relationship could be static or dynamic. In the static configuration, it behaved as a "cascaded menu" choice system and was used to feed the feedback module only with the options available at the moment (i.e. current menu). In the dynamic configuration, an intelligent agent tried to learn from use which would have been the most probable choice the user will make. The user could select the commands and monitor the system behavior through a graphical interface (Fig. 3)

Fig. 3. A possible appearance of the feedback screen (icons in the graphical interface), including a feedback stimulus from the BCI (cursor moving on a screen towards a given target that is controlled by the user)

The prototype system allowed the user to operate remotely electric devices (e.g. TV, telephone, lights, motorized bed, alarm, and a front door opener) as well as monitoring the environment with remotely controlled video cameras. While input and feedback signals were carried over a wireless communication, so that mobility of the user was minimally affected, most of the actuation commands were carried via a powerline-based control system.

4.3 Robot Control

The non-invasive BCI technology has been successfully integrated with a complex robotic device for the continuous "mental" control of a wheelchair. This integration was one of main achievement of the MAIA (FP6-003758) project [25]. In this type of human-computer interaction via BCI technology, the subject was confronted with a display which simulated the robotic wheelchair, being in a first person view. The subjects were instructed to execute three mental tasks (imagination of movement, rest, and words association), and 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. In successive experiments, the subject was asked to mentally drive both a real and a simulated wheelchair from a starting point to a goal along a pre-specified path. 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, subjects participated in a second experiment where he was asked to drive the simulated wheelchair following 10 different complex and random paths never tried before. 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.

5 Open Issues: Transducer Features, Real World Applications, and Standardization

Current research in the BCI field faces advancements in several aspects of its functioning. Here we will outline three main categories: intrinsic features of the BCI Transducer, deployment of BCIs in real world settings, theoretical modeling and standardization.

Improving intrinsic features of the BCI transducer may regard many aspects, such as increasing the transfer rate of information, improving classification accuracy, speeding up training and calibration phases, addressing the "illiterates" issue. All of these issues are important as they can furnish disabled people a communication mean that is as much similar as possible to that of heal people and can lighten the communication load for them.

Also, as the main purpose of BCI system is to help people to achieve some degree of independence in their daily life, usability of the interface in a non-laboratory setting is a fundamental aspect to consider and cannot prescind from the reduced obtrusiveness of sensors, the ease of configuration and operation, the on demand operability, dependability, portability and robustness of physical devices.

The last open issue regarding BCI systems is the need of a theoretical model that is able to describe all the features of different BCI implementations and of a standardization of all the BCI-related components that can create a common BCI language.

Formal models have been proposed to describe the general functioning of a BCI system [16, 26]; these models are important because they separately identify the main functional BCI blocks in all their functions and allow for combining and tuning them according to the final applications. In particular, the model defined in [26] describes, with unique static and temporal structures, different BCI implementations currently available in the literature, thus demonstrating that a unification of resources, and so their dissemination, in BCI research is possible. A standard model, in fact, leads to standards modules, for the implementation of BCI systems that can be independently designed and then matched or replaced according to the final application. Particular components of that standard should be interchangeable and independent (so different versions of each can be used without changes anywhere else in the system). Standards modules can finally lead to low-level technical standards that are not less important than the previous ones: for example, certain technical aspects, such as the layout of electrode connectors, are somewhat arbitrary. Because connectors are a mature technology, the definition of a standard for electrode connectors would provide the advantage of standards (i.e., improved interoperability) without being impacted by the disadvantage of that standard (i.e., stifled innovation in the area of electrode connectors). Technical standards have advantages and disadvantages that need to be considered. Use of technical standards can improve interoperability of components and thereby generally lessen the need for development and use expertise. FDA/CE certification is typically less costly. Technical standards might also provide the foundation to help solve possible future legal disputes arising from BCI development. On the other hand, technical standards might also stifle innovation in any area defined by a particular standard. Therefore, the choice of which areas should be standardized is an important one. In summary, standards should be chosen so that they specify only the interface between, but not the specific implementation of, particular BCI system components

The standard should facilitate interaction among researchers. It should be practical so that it can facilitate diffusion and should not be covered by intellectual property protection such as patents.

6 Conclusions

BCI research is a highly interdisciplinary field. Input is needed from clinical, engineering, neuroscience, psychology, and other fields, and interdisciplinary collaborations are required for further progress in BCI development.

BCI offers an unusual and compelling testing ground for new interaction ideas in the HCI field. In fact, BCI control is characterized by unusual properties, when compared to more traditional inputs: long delays, noise with varying structure, long-term drifts, event-related noise, and stress effects. The current remedy to this is constituted by post hoc processing the BCI signal so that it better conforms to traditional control. Another possible long term approach is to devise novel interaction modalities. BCI should not be treated as if it were a “noisy” mouse; rather, unconventional interaction paradigms should be explored, independently from “Windows, Icons, Menus and Pointing devices” (WIMP) interfaces. This approach is a crucial cross-point in the SM4ALL[27] project, in which the one of the goals related to BCI is to go beyond command/execute but rather to infer user's intention based on probabilistic notions and contextual information.

Finally, a BCI technology could monitor the subject mental state (i.e. stress, detection of errors, attention) and adapt the dynamics of interactions appropriately. This novel approach represents a fundamental step in the TOBI [28] project, where the BCI technology will be moved towards applications in real life context.

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