Approaches to EEG-based Brain-Computer Interfaces: A Survey

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Abstract. This survey presents a new classification of the *state of the art* approaches to electroencephalography-based brain-computer interfaces, resulting in twelve EEG-based BCI paradigms. A historical overview of the BCIs was included as complementary information. This work also presents the corresponding description and features of each approach. Also, this survey presents a comparison of the most popular electroencephalography recording methods, highlighting their advantages and showing their disadvantages. In order to clarify the similarities and differences of the analyzed approaches and systems, two comparative tables are presented, one for the paradigms and one for the recording systems.

Keywords: Brain-computer interfaces, electroencephalography, paradigms.

1 Introduction

Brain-computer interfaces (BCI) are real-time computer-based systems that translate brain signals into predefined and useful commands that can improve the human-computer interaction as well as improve the communication with other people [10,17]. BCIs are commonly developed to provide an alternative communication tool for people with severe neuromuscular disorders such as amyotrophic lateral sclerosis, spinal cord injury, and brainstem stroke [10]. There are several methods to acquire useful data from the brain, those methods could be invasive or non-invasive. Some examples of the invasive methods are the electrocorticography (ECoG) and the microelectrode arrays (MEAs). On the other side, non-invasive methods are the widely used due to its noninvasiveness, high temporal resolution, portability and reasonable cost [10,33], this category includes electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI) and near-infrared spectroscopy (NIRS), being the non-invasive EEG-based BCIs the objective of this survey, this approach is the most widely researched due to their minimal risk and the relative convenience of conducting studies and recruiting participants [17].

The purpose of this survey is to analyze the different approaches reported in the *state-of-the-art* brain-computer interfaces, as well as present an updated classification of these approaches, this work does not aim to present the results of the different paradigms, however the results of the papers that belongs to each paradigm were evaluated in depth. This survey is organized as follows: First, the *State of The Art* section presents a historical point of view. Second, an analysis of all the existing EEG-based paradigms is presented in the *Paradigms of EEG-based BCIs* section, based on the proposals of Cervantes et al. [4], Fernandez-Fraga et al. [6] and Hwang et al. [10], adding some updates and a summary table of paradigms and their corresponding description. Third, the section *Data Acquisition* presents a summary of the actual EEG recording methods used in EEG-based BCIs. The last sections contain *Conclusions* and *References*.

2 A short history of brain-computer interfaces

In 1988, Farwell and Donchin [5] presented the first P300-based BCI, they measured a positive potential in the EEG about 300 ms after the subject attended the target stimulus, this potentials serves as the control signal. The stimulus that elicit the P300 is detected by averaging the EEG responses to relatively rare presentations of the target stimulus interspersed with several non-target stimuli [6,21]. The Farwell and Donchin experiments consisted in a 6 x 6 matrix, that contained letters and other symbols, the subjects could select items from the matrix by the average response to the flash of the target item, which differed from the average responses to the other items [6]. Many P300-based studies have been published [3,10,16,20,21,26,28]. The P300 potentials can also be elicited by auditory stimuli and several research groups have explored this option [8,15,13].

Another approach to brain-computer interfaces explodes the sensorimotor rhythms (SMRs) as control signals in the BCI. This approach was first reported by Wolpaw et al. in 1991 [31]. SMR signals are μ and β oscillations, that are recorded over sensorimotor cortices, the μ and β oscillations change in amplitude with movement, imagined movement or preparation for movement [6]. SMR-based BCIs can control a cursor to hit targets on a screen or perform several computer-based tasks, users can learn how to control the SMR amplitudes by increasing or decreasing the amplitude of the rhythms. Many of the works with SMR-based BCIs consist in asking the user to generate specific mental states (by imagining physical movement), which is commonly called motor imagery (MI). Several research articles have been published around this approach [2,12,27,30,31].

Over time new approaches and techniques emerged, such as visually-evoked potentials (VEPs), steady-state visually evoked potentials (SSVEPs), error-related potentials (ErrPs), each of these having sub-categories with important results [10]. VEPs and SSVEPs are based in potentials that are elicited by visual content, the first approach to the analysis of these potentials was reported by Sutter E. [25] in 1992, and his publication was followed by many others in the area [1,11,20,24,23,29].

Successful brain-computer interfaces systems are commonly an hybrid between various paradigms, typically researchers try to eliminate the weaknesses of one approach by combining the strengths of various approaches. In 2012, Spüler presents an hybrid BCI based on visually evoked potentials and improving the performance with an adaptation based on error-related potentials [24]. This decade shows a trend in the research of this hybrid systems can be seen: Yin et al. proposed a hybrid BCI that incorporates SSVEP into the P300 paradigm [32], also Li et al. reported an controlled wheelchair by combining P300 and SSVEP paradigms [14]. Most recent works in hybrid BCIs are interesting too, in 2019, Niknamian S. proposed a hybrid system between SSVEP and P300 to enhance the accuracy of a speller system [19]. Also, in 2019, Machado M. presented a hybrid system that combines visual and auditory stimuli [15]. In late 2019, Oralhan Z. published a paper with another hybrid method, an approach for a speller BCI based on P300 and SSVEP.

3 Paradigms of EEG-based BCIs

BCI systems may be classified in two main categories: endogenous and exogenous systems [4]. Endogenous systems are dependent of the user's ability to control their electrophysiological activity, sensorimotor rhythms (motor imagery or MI) based systems and Slow Cortical Potential (SCP) based systems belong to this category. MI systems are based on the imagery of performing motor actions to evoke signals similar to those observed in actual movement and SCP systems involve slow changes in voltage generated on the cerebral cortex, with a duration between 0.5 s and 10 s, SCP-based systems are also associated with movement. Endogenous systems require a period of intensive training [6]. The exogenous systems obtain the data from evoked related potentials (ERP), these systems depends on the electrophysiological activity triggered by external stimuli [6]. Exogenous systems are easily to master than endogenous systems and are based in the acquisition of data from evoked related potentials (ERP): P300 events, visual evoked potentials (VEP), steady-state visual evoked potentials (SSVEP) or auditory evoked potentials (AEP).

Also, BCI systems may be classified according to the experimental paradigm employed to elicit different kinds of brain activities [6,10]. Hwang et al. [10] proposed the following seven categories: motor imagery, visual P300, steady-state visual evoked potential (SSVEP), non-motor mental imagery, auditory, hybrid and other paradigms. Hwang et al. includes covert attention, motion-onset visual evoked potentials (MOVEP), flash onset and offset visual evoked potentials (FOVEP), and error related potentials in their "other paradigms" section. Fernandez-Fraga et al. [6] proposed a little different classification with five categories: evoked potential by P300 events, visually evoked potential (VEP), steady-state visual evoked events (SSVEP) and auditory evoked potential (AEP). Table 1 summarizes all the paradigms and its corresponding description.

4 Data acquisition

A functional EEG-based BCI requires reliable, robust and high-quality EEG recording systems. There are several varieties of recording methods, the standard recording uses wet electrodes. Wet electrodes use a conductive gel that maintains good electrode contact with the scalp, what provides an excellent EEG recording. Unfortunately, wet electrodes are not optimal or practical for long-term daily use, this kind of electrodes require a careful application; the gel is sometimes messy and needs periodic replenishment; the cap or other apparatus that hold the electrodes in their side may be uncomfortable, awkward or unattractive [17]. Furthermore, wet electrode-based EEG systems

Table 1. Summary of the existing BCI paradigms. The table presents a short description of each paradigm. The listed paradigms are not necessarily different, some paradigms in the table are subsets of others but they have characteristics that must be distinguished.

Paradigm	Description
Motor imagery	Based on the imagery of performing motor actions to evoke signals in the brain. Commonly consists in the imagination of kinesthetic movements of several parts of the body. The origin of the signals depends on the imagined activity.
P300 Events	Works over event-related potentials evoked by infrequent and task-relevant stimuli. Some of the stimulus have a relationship with the intention of the subject. The potential appears around 300 ms after each stimulus. These signals are measured most strongly in the parietal lobe.
Visual P300	Visual P300 is a kind of P300 event-related potential, with the difference that the stimuli are strictly visual.
VEP	Visually evoked potentials are detected on the EEG after the presentation of the visual stimulus. These kind of responses are usually originate from the occipital cortex of the brain.
SSVEP	Steady-state visual evoked potential is a periodic brain response evoked by a special stimuli: repetitive presentation of flickering or reversing visual stimulus. These potentials are also detected on the EEG after the presentation of the visual stimulus.
Non-motor MI	Consists in mental imagery tasks excluding motor imagery tasks. Mental calculations, remember images or faces, internal singing or speech and spatial navigation are good examples of the stimuli in this paradigm.
AEP	Auditory event potentials are perceived after the presentation of the auditory stimulus, commonly sounds at different frequencies, when the subject concentrates on any of them, a potential of the same frequency as the stimulus is generated.
Covert attention	Covert attention is defined as paying attention without moving the eyes to the point of that location. These tasks often require participants to observe a number of stimuli, but attend only one.
MVEP	Motion onset/offset visual evoked potentials are visual evoked potentials related to global motion during a visual motion discrimination task. These tasks consist in the discrimination of onset or offset motion in the stimuli.
FVEP	Flash onset/offset visual evoked potentials are the signals generated by a flashing stimuli, such as digits or letters that are displayed on a screen. Subjects can shift their gaze to the flashing target to induce a FVEP.
ErrP	Error related potentials (ErrPs) are the responses generated by the brain when the subject recognizes an error during a task. ErrPs are widely studied for error correction or adaptation in BCIs.
Hybrid	This category includes the simultaneous use of more than two paradigms mentioned in this table.

are susceptible to a variety of artifacts due to the non-brain activity, such as electromyographic signals (EMG), bodily movements or nearby electrical equipment [17].

Table 2. Summary of EEG recording methods. The first column indicates the commercial name of the recording system as well as its model, the second column describes the type of electrodes that the system uses, the third column presents a set of advantages taken from several papers where these systems were used and the fourth column presents disadvantages reported in the literature.

System	Type of electrode	Advantages	Disadvantages
BioSemi ActiveTwo	Active wet	Excellent EEG recording quality Up to 280 channels Does not limit electrode location Very low impedance	Uncomfortable Not optimal for long-term use Very expensive
Emotiv EPOC	Moistened felt pads	Semi-rigid support Fast electrode placement Low-cost 14 channels	Less accurate than wet methods Restricted electrode placement Susceptible to EMG signals
g.SAHARA	Active dry	Does not limit electrode location Similar quality to wet electrodes Easy to use 8-64 channels	Could be uncomfortable
g.SCARABEO	Wet	Excellent EEG recording Does not limit electrode location 8-64 channels	Messy conductive gel Sensible to noise Not optimal for long-term use
B-Alert X10	Wet	Good EEG recording quality Ambulatory Does not limit electrode location	Maximum 9 channels
Wearable Sensing DSI-Hybrid	Active dry	Easy to use Fast electrode placement Similar quality to wet electrodes Analyzes BOLD actibity	Non-cosmetic Could be uncomfortable Awkward
QUASAR DSI 10/20	Dry	Comfortable Ambulatory Long-term comfort 21 channels	Less accurate than wet methods Awkward Non-cosmetic

4.1 Electrode types

Due to the weaknesses of the wet electrode-based EEG recordings, several wet alternatives as well as dry electrodes have appeared in the last decade. One of the most used EEG recording system is the Emotive EPOC: a 14-channel system that uses moistened felt pads instead the common conductive gels, mounted on a semi-rigid support that allows a quick and comfortable placement of the electrodes, but is less accurate than the conventional supports. Emotive EPOC systems are relatively cheap in comparison with other recording systems. An alternative to wet electrodes is the g.SAHARA system, a dry electrode that consists of a set of 8 pins, which mounted in a conventional cap does not limit electrode locations and provide similar results to the systems that uses wet electrodes. The BioSemi ActiveTwo systems use active wet electrodes, and provide excellent EEG recording quality, these systems allow up to 280 channels. Nijboer et al. [18] reported that a 32 channel version produced a P300-based accuracy higher than the g.SAHARA and EPOC systems. The EPOC and g.SAHARA electrodes rely on low impedance resistive contact with the scalp, while the dry electrodes of the QUASAR systems use a hybrid combination of high impedance resistive and capacitive contact with the scalp [22]. Hairston et al. reported that the EPOC and QUASAR systems could produce uncomfortable pressure points and movement artifacts [7], they also reported that dry electrode-based systems can be more difficult to secure to the scalp, crating a trade-off between comfort and recording quality. Table 2 summarizes several EEG recording systems, classified by the type of electrodes they use.

4.2 Electrode holders

On the other hand, the device that holds the recording electrodes on the scalp is extremely important in the long-term home use. An ideal electrode holder device should allows electrodes to be accurately positioned in the scalp, allowing every possible position and ensuring that the electrodes will be firmly placed, all of this without sacrificing comfort and being non-intrusive and cosmetic. ”Insecure electrode placement can lead to noise due to sudden changes in impedance (”electrode pops”) and variable placement can increase day-to-day variations in the EEG features used by a BCI”, McFarland and Wolpaw [17] say.

5 Conclusions

Although the main focus of this survey is to establish a new classification of the existing paradigms to build brain-computer interfaces, the systems that use invasive EEG-recordings were not treated in depth. The invasive techniques that uses epidural or subdural electrodes or intracortical microelectrodes have more disadvantages than advantages. Although these techniques offer more secure placement and better spatial resolution that non-invasive techniques, their invasive nature and increased costs and risks are not well justified since there are methods with zero-invasiveness that can produce comparable quality and target acquisition times [17], making them a more viable, economical and accurate option. In addition, these invasive methods have not yet demonstrated reliable long term stability [9].

Focusing on the non-invasive methods, which are primarily treated in this survey (due to its excellent invasiveness-quality-price ratio), the trend is that these systems sometimes sacrifice comfort for quality and vice versa, and sometimes sacrifice accessibility for quality and accuracy as in BioSemi systems (which are very expensive). The Emotiv EPOC systems are less accurate than conventional electrode holders and restricts the possible electrode placements in the scalp, what results in a higher susceptibility to EMG contamination but that disadvantages are compensated by their connectivity, comfort, cosmetic design and relatively low cost. Newer technology as the g.SAHARA dry electrodes can provide a similar results to those provided by wet electrodes by sacrificing comfort and aesthetic. The g.SCARABEO systems provide an excellent EEG recording, with a good channel range and permissive electrode location, but is slower to set up when comparing with other systems and the conductive gel could be messy, resulting in a non-suitable system for long therm use. The selection of any acquisition technique will depends on a balance of a variety of variables: target quality, noise tolerance, comfort, long-term capabilities and budget.

Most EEG-based BCIs use evoked potentials as the control signals, primarily P300 evoked potential, sensorimotor rhythms or steady-state visual evoked potentials. Even so, there are several interesting approaches such as non-motor mental imagery, auditory evoked potentials or error-related potentials. Hybrid systems that used two or more of these paradigms together seem to have good results since the researchers use different paradigms to eliminate weaknesses.

Better EEG-recording systems that provide stable high-quality signals, that are comfortable and easy to use will improve the actual brain-computer interfaces. On the other hand, better algorithms and signal processing techniques that improve the performance and the accuracy of the BCIs are needed. Dry electrode systems and new machine learning algorithms have considerable promise.

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