Expert Systems With Applications ©Elsevier
Accepted version of an article published in Expert Systems With Applications, vol. 120, 2019, pp. 155-166
DOI: https://doi.org/10.1016/j.eswa.2018.11.026

Towards an Accessible Use of Smartphone-Based Social Networks through Brain–Computer Interfaces

Víctor Martínez-Cagigal[1,*], Eduardo Santamaría-Vázquez, Javier Gomez-Pilar, Roberto Hornero

Biomedical Engineering Group, E.T.S.I. Telecomunicación, University of Valladolid, Paseo de Belén 15, 47011, Valladolid, Spain

Abstract

This study presents an asynchronous P300-based Brain–Computer Interface (BCI) system for controlling social networking features of a smartphone. There are very few BCI studies based on these mobile devices and, to the best of our knowledge, none of them supports networking applications or are focused on an assistive context, failing to test their systems with motor-disabled users. Therefore, the aim of the present study is twofold: (i) to design and develop an asynchronous P300-based BCI system that allows users to control Twitter and Telegram in an Android device; and (ii) to test the usefulness of the developed system with a motor-disabled population in order to meet their daily communication needs. Row-col paradigm (RCP) is used in order to elicitate the P300 potentials in the scalp of the user, which are immediately processed for decoding the user's intentions. The expert system integrates a decision-making stage that analyzes the attention of the user in real-time, providing a comprehensive and asynchronous control. These intentions are then translated into application commands and sent via Bluetooth to the mobile device, which interprets them and provides visual feedback to the user. During the assessment, both qualitative and quantitative metrics were obtained, and a comparison among other state-of-the-art studies

*Corresponding author
Email addresses: victor.martinez@gib.tel.uva.es (Víctor Martínez-Cagigal), eduardo.santamaria@gib.tel.uva.es (Eduardo Santamaría-Vázquez), javier.gomez@gib.tel.uva.es (Javier Gomez-Pilar), robhor@tel.uva.es (Roberto Hornero)
[1] *Phone number:* +34 983 18 47 16

was performed as well. The system was tested with 10 healthy control subjects and 18 motor-disabled subjects, reaching average online accuracies of 92.3% and 80.6%, respectively. Results suggest that the system allows users to successfully control two socializing features of a smartphone, bridging the accessibility gap in these trending devices. Our proposal could become a useful tool within households, rehabilitation centers or even companies, opening up new ways to support the integration of motor-disabled people, and making an impact in their quality of life by improving personal autonomy and self-dependence.

Keywords: Brain-computer interface (BCI), smartphones, asynchronous control, social networks, P300 event-related potentials, electroencephalography (EEG).

---

1. Introduction

Brain–Computer Interfaces (BCI) are able to establish a communication system between our brains and the environment, making it possible to control devices with our brain signals. Such bypassing requires the monitoring of brain activity, which is commonly accomplished using electroencephalography (EEG) due to its portability, non-invasiveness, and low-cost (Wolpaw et al., 2000). Hence, electric potentials are recorded by placing a set of electrodes over the user's scalp (Wolpaw et al., 2000, 2002). The main motivation of BCI systems has always been to improve the quality of life of motor-disabled people, which usually contributes to reduce the accessibility gap in different fields. Thus, end users can take advantage of this novel technology to reduce their dependence, regardless of their disability. These motor-disabilities could have been caused by neurodegenerative diseases, traumas, muscle disorders, or any illness that impair the neural pathways that control muscles or the muscles themselves (Wolpaw et al., 2000, 2002; Kübler et al., 2007; Kübler and Birbaumer, 2008). Moreover, BCI systems may use a wide variety of control signals to detect the user's intentions in real time (Wolpaw et al., 2002). In particular, exogenous signals, such as P300 evoked potentials, are commonly used to assure the efficacy of the systems with any motor-disabled user. These potentials are produced in response to infrequent and particularly significant stimuli about 300 ms after their onset (Wolpaw et al., 2002).

The rapid growth of the Internet in the last decades has caused a huge impact on people's lives, bringing entirely new ways of everyday communication. This impact has been enlarged by the popularity of the smartphones, which provide a continuous Internet connection. In fact, it is estimated that there are 4.9 billion of unique mobile users in the world, reaching a market penetration of 66% (Kemp, 2017). Their functionalities cover from managing finances to reading news, including watching videos, shopping, playing games or searching for information. However, it is worthy to note that more than the 56% of the time spent is dedicated to socializing (i.e., social media and instant messaging), both in everyday and working environments (Ipsos MORI and Google, 2017). Currently, there are 2.8 billion of active social media users, and 91.4% of them access social media with their smartphones or tablets (Ipsos MORI and Google, 2017). Despite this development, the accessibility of these devices is still restricted for motor-disabled people that are unable to use accurately their hands and fingers.

Motor disabilities comprise the limitations on people's physical functioning that hinder their full and effective interaction with the environment and society (World Health Organization, 2011). These impairments may be caused by: (i) neurodegenerative diseases, such as multiple sclerosis, amyotrophic lateral sclerosis, Friedreich's ataxias, etc.; (ii) congenital conditions, such as cerebral palsy, polymalformative syndromes, myotonic dystrophies, etc.; or (iii) traumas, such as strokes or spinal cord injuries, among others. It is estimated that the world average prevalence rate of disability for adult people is 15.6%, which ranges from 11.8% in higher income countries to 18.0% in lower ones (World Health Organization, 2011). Moreover, diseases and traumas are not the only cause that can lead to develop a motor disability, but also the natural ageing contributes in a high extent. In fact, older people are disproportionately represented in disability populations and thus, everybody is susceptible to develop a motor disability at some point in their lives (World Health Organization, 2011). In this respect, BCI applications represent a novel technology from which disabled people can benefit to reduce their dependence.

From an expert and intelligent systems point of view, BCIs utilize artificial intelligent techniques to replace, restore, enhance or supplement the natural central nervous system outputs of their users (Hill and Wolpaw, 2016). To this end, BCIs should comprise a decision-making stage that interprets neural activity and determines users' intentions or emotions. Moreover, several BCIs include an adaptive engine that learns from the experience, modifying classifier weights and features while the user controls the system (Atkinson and Campos, 2016). These systems can be trained to react to changes in the EEG signals that could reflect: (i) emotions (Blondet et al., 2013; Atkinson and Campos, 2016), (ii) road drowsiness (Da Silveira et al., 2016), (iii) driving stress (Chen et al., 2017), (iv) mental effort (Zammouri et al., 2018), (v) attention (Aloise et al., 2011; Pinegger et al., 2015; Martínez-Cagigal et al., 2017a), (vi) motor imagery (Wolpaw et al., 2002), or (vii) event-related responses (Luck, 2014), among others. Accordingly, BCIs play a potential role as knowledge-based systems in many clinical and industrial applications.

In recent years, some studies have attempted to apply BCI systems to mobile devices with the aim of controlling a wheelchair (Jayabhavani et al., 2013), robots (Ma et al., 2015), or detecting the user's emotions (Blondet et al., 2013). Despite the popularity of the smartphones and tablets these days, there are very few studies in the scientific literature that aim to control any of their functionalities. These studies are limited to dial numbers in cell phones (Wang et al., 2011; Chi et al., 2012), accept incoming calls (Katona et al., 2014), call contacts (Campbell et al., 2010; Wang et al., 2011), spell words (Obeidat et al., 2017; Elsawy et al., 2017), or play a simple racing game (Wu et al., 2014). Possibly the work of Elsawy and Eldawlatly (2015) is the one that relates more closely to the topic, which allows users to open pre-installed apps and visualize the image gallery. Nevertheless, to the best of our knowledge, none of those studies has been focused on providing a high-level control of a smartphone or tablet, nor making social apps accessible to disabled people. Furthermore, it is well known that disabled users generally reach lower accuracies than healthy users (Wolpaw et al., 2002; Sellers and Donchin, 2006; Martínez-Cagigal et al., 2017a) and thus, the assessment of BCI systems with end users is essential for ensuring a fair evaluation. Since these studies have not been tested with a disabled population, their reliability may be compromised in real life situations.

The purpose of this study is twofold: (i) to design and develop a practical BCI-based application that allows disabled people to access social media with any smartphone or tablet; and (ii) to evaluate it with a population of motor-disabled people in order to assess the usefulness of our proposal to meet their daily communication needs. With the objective of providing a comprehensive social networking support, we consider that the system should implement both a social network and an instant messaging applications. In this case, the application will provide a complete control of Twitter and Telegram, which currently have more than 317 and 100 millions of mobile

Table 1: Demographic and clinical data of the participants

	User	Sex	Age	DD	Disease
Motor-Disabled subjects	**M01**	F	48	90%	Stroke
	M02	M	46	80%	Spinal cord injury
	M03	F	38	93%	Friedreich's ataxia
	M04	M	39	98%	Spinal cord injury
	M05	F	49	78%	Friedreich's ataxia
	M06	M	31	76%	Cerebral palsy
	M07	M	52	99%	Cerebral palsy
	M08	M	44	90%	Friedreich's ataxia
	M09	M	47	69%	Cerebral palsy
	M10	M	67	87%	Cerebral palsy
	M11	M	62	86%	Myotonic dystrophy
	M12	M	47	90%	Polymalformative syndrome
	M13	F	66	94%	Friedreich's ataxia
	M14	F	40	88%	Friedreich's ataxia
	M15	M	38	98%	Spinal cord injury
	M16	M	50	80%	Spinal cord injury
	M17	F	42	89%	Cerebral palsy
	M18	F	45	84%	Spinal cord injury
Control subjects	**C01**	M	25	0%	-
	C02	M	25	0%	-
	C03	M	24	0%	-
	C04	M	25	0%	-
	C05	M	25	0%	-
	C06	M	32	0%	-
	C07	M	24	0%	-
	C08	M	25	0%	-
	C09	F	23	0%	-
	C10	F	33	0%	-

F: female, M: male, DD: degree of disability.

active users, respectively (Kemp, 2017). Moreover, the application will monitor users' attention and apply a dynamic asynchronous control management (Martínez-Cagigal et al., 2017a). As a result, the expert system will only deliver conscious selections, eliminating the need of read-mode commands or external supervisors.

2. Subjects

Eighteen motor-disabled subjects (MDS, mean age: 47.63 ± 9.53 years; 11 males, 8 females) and ten healthy control subjects (CS, mean age: 26.10 ± 3.45 years; 8 males, 2 females) were included in this study. MDS participants were recruited from the National Reference Centre on Disability and Dependence, located in León (Spain). All subjects gave their informed written consent to participate in the study, previously approved by the local ethics committee. Table 1 summarizes the clinical and demographic characteristics of all participants. As can be noticed, all MDS present moderate or high degrees of motor disability (mean: 86.42% ± 8.58%), caused by different diseases: stroke (1), spinal cord injuries (5), Friedreich's ataxias (5), cerebral palsies (5), polymalformative syndrome (1), and myotonic dystrophy (1).

3. Methods

As shown in Fig. 1, the developed BCI application involves three main entities, which communicate among themselves: (i) the user, which involves the EEG signal acquisition; (ii) the laptop, which generates the visual stimuli, processes the signal, decodes the user's intentions and translates them into commands; and (iii) the mobile device, which interprets those commands and provides visual feedback to the user. The methodology that is applied to each stage, as well as the evaluation procedure, are described below.

3.1. Signal acquisition

EEG signals from users were recorded using eight active electrodes, placed on Fz, Cz, Pz, P3, P4, PO7, PO8 and Oz, according to the International 10–20 System distribution (Jasper, 1958). The system was referenced to the earlobe, using the Fpz electrode as a ground. Electrodes were connected to a g.USBamp amplifier (g.Tec, *Guger Technologies*, Austria) with a sampling frequency of 256 Hz. As a pre-processing stage, band-pass (0.1–60 Hz), notch (50 Hz) and common average reference (CAR) filters were applied. BCI2000 platform was used to record the data, display and process the stimuli (Schalk et al., 2004).

3.2. Signal processing

The exogenous nature of P300 evoked potentials avoids training (Wolpaw et al., 2002). Furthermore, the number of different commands that can

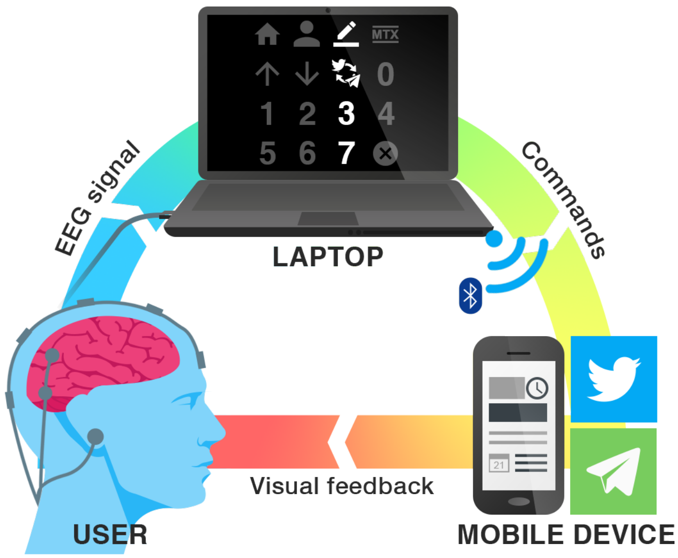

Figure 1: Structure of the BCI social network application. The EEG signal of the user is sent to the laptop, which processes it, decodes the user's intentions and translates them into commands in real time. These commands are finally sent to the device (i.e., smartphone or tablet) via Bluetooth, which interprets them and provides visual feedback to the user.

be selected by the user is extremely large whether the *odd-ball* paradigm is used (Farwell and Donchin, 1988; Wolpaw et al., 2002; Martínez-Cagigal et al., 2017a). In this paradigm, an infrequent target stimulus, which has to be attended, is presented among other distracting background stimuli that have to be ignored. When the user attends to the target stimulus, a P300 potential appears mainly on the parietal and occipital cortex (Farwell and Donchin, 1988; Wolpaw et al., 2002; Martínez-Cagigal et al., 2017a). We used an extension of the *odd-ball* paradigm, known as row-col paradigm (RCP), for decoding the users' intentions (Townsend et al., 2010). In the RCP, a matrix containing the commands that control the BCI application is displayed, whose rows and columns are randomly flashed. The user, who has to stare at the desired command, will generate a P300 potential when the target's row or column is illuminated (Farwell and Donchin, 1988; Wolpaw et al., 2002; Townsend et al., 2010; Martínez-Cagigal et al., 2017a; Martínez-Cagigal and Hornero, 2017; Obeidat et al., 2017).

Social media apps in general and, particularly, Twitter and Telegram, have some key functionalities that should be controlled. In this regard,

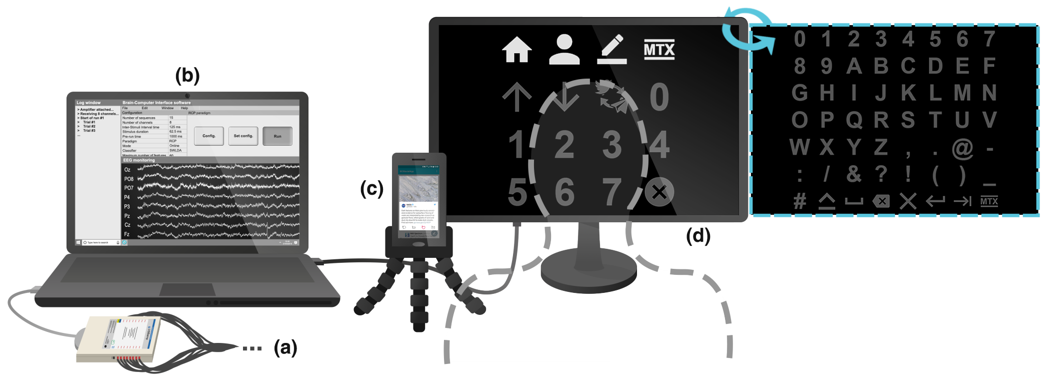

Figure 2: Evaluation setup from the point of view of the user: (a) EEG acquisition unit, (b) laptop that monitors the EEG signal, processes it and generates the stimuli; (c) smartphone on a small tripod, close enough to the user for receiving the visual feedback; (d) panoramic screen that displays the stimuli. Both matrices are depicted: (left) main matrix, whose first row is currently flashed; and (right) keyboard matrix, which can be toggled by the user through the "MTX" command.

owing to the fact that not only the RCP matrices have to include control commands, but also alphanumeric characters and symbols, our application uses alternatively two different matrices: (i) main matrix, and (ii) keyboard matrix (see Fig. 2). The first one is intended to control the main functionalities of Twitter and Telegram, such as loading the home view, opening a new *tweet* or chat, visualizing a profile or contact, toggling between both social networks or scrolling the current view. The second one, by contrast, is intended to write texts and fill out forms. Both matrices can be freely toggled between themselves if the user selects the command "MTX".

Due to the high sampling rate of the EEG recordings relative to the low frequency of the P300 potential response, a dimensionality reduction is beneficial for the real-time classification (Krusienski et al., 2008). In order to extract the most relevant features of the EEG signal, a sub-sampling of 20 Hz is applied on the first 800 ms from the stimulus onset (i.e., 16 samples per stimulus and channel). Then, channels are concatenated, returning a vector of 128 features per stimulus (Corralejo et al., 2014; Martínez-Cagigal et al., 2017a). Afterwards, the extracted feature vectors of each stimulus are processed by a linear classifier, which determines the presence (i.e., positive class) or the absence (i.e., negative class) of a P300 evoked potential. Stepwise linear discriminant analysis (SWLDA) was used in this study, with $p_{in} = 0.10$ and $p_{out} = 0.15$ as selection/elimination criteria and a maximum of 60 selected features for each input vector (Krusienski et al., 2006, 2008; Corralejo et al., 2014; Martínez-Cagigal et al., 2017a; Martínez-Cagigal and Hornero, 2017). Even though SWLDA has a simple implementation, it delivers similar performances and lower computational cost in comparison with more complex methods, which makes it a popular algorithm for the P300 classification problem (Krusienski et al., 2006, 2008; Blankertz et al., 2011; Zhang et al., 2016; Martínez-Cagigal et al., 2017b). This method calculates a projection of the input data that simultaneously minimizes the within-class and maximizes the between-class covariances (Keinosuke, 1990). Thus, the probability score of finding a P300 in the i-th illumination is computed using the Euclidean distance between the projected data and the projected mean of the positive class (Narsky and Porter, 2013), as follows:

$$l_i = 1 - \|\langle \mathbf{w}, \mathbf{x}_i \rangle - \langle \mathbf{w}, \mu_i \rangle\| \tag{1}$$

where $\mathbf{w}$ is the weight vector, computed in a calibration session; $\mathbf{x}_i$ denotes the feature vector, and μ_i the mean of the positive class. The probability of selecting a certain command j is computed as the average of the scores of all the stimuli that belong to its row and column, as indicated in (2). Therefore, the output selected command is the one that provides the maximum average probability (i.e., $p_s = \max \mathbf{p}$) (Martínez-Cagigal et al., 2017a).

$$p_j = \frac{1}{N} \sum l_{i \in row \cup col} \tag{2}$$

RCP-based matrices are synchronous processes, which means that the system will deliver a selection even if the user is not paying attention to the visual stimulation (Aloise et al., 2011; Pinegger et al., 2015; Martínez-Cagigal et al., 2017a). This fact severely restricts the autonomy of the application, needing an external supervisor or implementing a read-mode command that could pause the system for a fixed number of seconds. In our application, we have implemented a dynamic asynchronous control management by monitoring the user's attention (Martínez-Cagigal et al., 2017a). The method works as follows: (i) EEG signals of the user paying attention (i.e., control state) and ignoring (i.e., non-control state) the stimuli are recorded in a calibration session; (ii) the signals are processed and the final selected command probabilities p_s are stored in both control and non-control arrays; (iii) the arrays are fed into a receiver operating characteristic (ROC) curve for determining the optimum threshold that maximizes the sensitivity-specificity pair; (iv) the custom threshold value T for each user is then used online. In the online

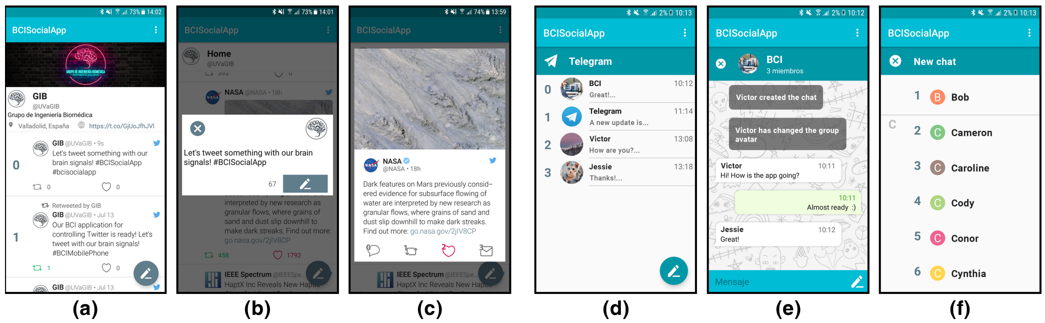

Figure 3: Snapshots of the BCI social networking application: (a) Twitter's profile timeline, (b) dialog for writing *tweets*, (c) *tweet* view, (d) Telegram's conversation list, (e) Telegram's group, and (f) contact list.

sessions, the selected command probability is compared with the threshold in real-time. If $p_s > T$, the selection is accepted and the command is sent via Bluetooth to the mobile device; otherwise, the selection is rejected and the system encourages the user to try to select the command again.

3.3. Application

It has been recently reported that 98.8% of the smartphones that are sold these days either use Android or iOS (International Data Corporation, 2017). In fact, Android has an 83.4% of the worldwide smartphone market share, while iOS has a 15.4% (International Data Corporation, 2017). For this reason, and taking into account that Android is a free open platform, we have developed our application for this operating system. Whether the application is used for the first time, the user is asked to login the Twitter account and to register the telephone number to Telegram. Switching between both services is also handled by a toggle command that can be selected by the user. Fig. 3 shows several snapshots of the final application, whose main functionalities are described below.

Twitter. Defined as a popular free social networking service that allows users to broadcast public small messages (up to 280 characters), known as *tweets*. Although it was originally developed as an online service, its mobile activity reaches more than 317 million of active users, which makes Twitter one of the most installed social networking services in smartphones or tablets nowadays (Kemp, 2017). Our BCI application implements the entire set of Twitter functionalities, including both the possibility of interacting with: (i) "tweets", writing, answering, "retweeting", or making them as favorite; and (ii) accounts, surfing among profiles, or sending direct messages.

Telegram. Defined as a non-profit cloud-based instant messaging service that allows users to send encrypted messages and exchange files of any type in real-time. Even though it has a desktop version, its popularity is extended thanks to the mobile application, which has more than 100 million of active users and has become the most popular instant messaging app in several countries (Kemp, 2017). Our BCI application covers its main functionalities, including the possibility of interacting with individual chats, groups and channels through real-time messages, or creating new chats with any contact that is stored in the device.

3.4. Evaluation procedure

The evaluation setup is depicted in Fig. 2. During the assessment, participants were sat on a comfortable chair or on their own wheelchair, in front of a panoramic screen, as well as in front of a smartphone on a small tripod. The screen was connected to a laptop (Intel Core i7 @ 2.6 GHz, 16 GB RAM, Windows 10), which executed the signal processing stage and sent the commands to the mobile device (Samsung Galaxy S7, 4GB RAM, Android 7.0) via Bluetooth. The assessment was composed by three different sessions: the first two intended to calibrate the system, and the last one intended to evaluate the BCI application.

Calibration 1. The first session was intended to compute the optimal parameters for each user, such as the number of sequences (i.e., repetitions of the stimuli), the classifier's weight vector, and the asynchronous threshold value. Firstly, users were asked to pay attention to 6 items in 4 different trials (i.e., to spell 4 words composed of 6 characters). Due to its larger size, the keyboard matrix was used and the number of sequences was fixed in 15. During this calibration, users were encouraged to count how many times the target character was being flashed, in order to keep attention to the task. After these runs, SWLDA was trained, returning the weight vector and the most appropriate number of sequences for each user. The latter is computed as the minimal number of repetitions that reaches a 100% of accuracy using the training data. Hereinafter, the trained SWLDA model and the optimal number of sequences for each user were used in the online sessions. Note that training data was composed of 5400 observations per subject (6 items $\times$ 4 trials $\times$ 15 seq. $\times$ [7 rows + 8 columns]). Then, the first stage of threshold calibration was performed. Composed of 8 trials with 6 items, the calibration was intended to record signals of both control and non-control states. Thus, users were asked to pay attention to 4 trials, and to ignore the flashings of the remaining 4 (e.g., by reading a text).

Calibration 2. The second session was intended to finish the threshold calibration for increasing the overall performance. The objective was to record additional data in order to create a most robust asynchronous threshold that could be adapted to the inter-session variability of the participants (Picton, 1992; Martínez-Cagigal et al., 2017a). Hence, users were asked to spell 4 trials and ignore 4 trials more, all of them composed by 6 items. It is noteworthy that both stages of the threshold calibration were performed using the main matrix, aiming to reduce the task time due to its smaller size. Then, thresholds for both sessions were calculated as the optimal points of the ROC curves using control and non-control classes. Finally, the optimal threshold value was computed as the average of them.

Evaluation. The third session was intended to assess the performance and the quality of the developed BCI system. The evaluation session, strictly online, was made up of 6 different tasks, whose difficulty increased progressively. It is worthy to mention that the duration of each task varied among users due to their different optimal number of sequences. These tasks are described below, together with the ideal number of selections and the matrices that are required to finish them.

i) Toggling between Twitter and Telegram. Using Twitter, users had to scroll down and up the timeline and toggle to Telegram (3 items, main matrix).
ii) Retweeting a *tweet*. Using Twitter, users had to scroll down the timeline, select one *tweet* and retweet it (4 items, main matrix).
iii) Writing a new *tweet*. Using Twitter, users had to open the form to write a new *tweet* and spell “hello” (7 items, both matrices).
iv) Checking the profile and answering a *tweet*. Using Twitter, users had to visit their own profile, select the last *tweet* and answer “great!” (11 items, both matrices).
v) Creating a new chat. Using Telegram, users had to select one contact, create a new chat, and spell “how are you?” (11 items, both matrices).
vi) Chatting with someone. Using Telegram, users had to select one chat

from the conversations list, in which the interlocutor had said: "hi! how are you?", and reply with "fine, and you?" (12 items, both matrices).

During the evaluation session, both quantitative and qualitative metrics have been registered. With regard to the quantitative measures, the number of correct selections, errors, sequences and the time that it takes to accomplish each task have been noted down. As a result, accuracies and output characters per minute (OCM) for each task have been calculated. Accuracy is defined as the percentage of correct selections to the total number of selections. It is worthy to note that the selections that have not overcome the asynchronous threshold have not been considered errors, since they have not been sent to the final device. OCM, calculated by dividing the total number of selections by the duration of the task, is an online metric that estimates the true communication rate of the system (Speier et al., 2013). Although information transfer rate (ITR) has traditionally been used in this respect, several authors pointed out that ITR makes assumptions that are usually incorrect in online BCI systems (Speier et al., 2013; Yuan et al., 2013). ITR assumes that: (i) all possible selections are equally probable, (ii) the system is memoryless, and (iii) a synchronous paradigm is used. In online systems where users are allowed to correct selection errors, ITR may return counter-intuitive results when two different users type the same word and one shows lower speed, but returns a higher ITR. Since correcting an error implies to successfully spell two or more commands, the ITR increases because the decrease in accuracy weighs less than the increase in extra selections. Moreover, ITR requires the number of possible selections (i.e., n), as well as the reached accuracy. Despite that the latter is a global metric, n varies if more than one RCP matrix is used, hindering the generalization of ITR values. In addition, ITR assumes that commands are sequentially selected following a constant speed, without pauses. Therefore, the estimation is biased in asynchronous-based BCI systems. It is also noteworthy that the ITR estimation is incorrect if the subject did not perform any error, returning an infinite value. According to this rationale, ITR is replaced by OCM considering the nature of the proposed BCI system.

Regarding the qualitative testing, users were asked to fulfill a questionnaire at the end of the session. The survey was composed of 20 items that had to be ranked in a 7-point Likert scale (Likert, 1932). These items assessed the subjective opinions of the users in regard to the application speed, interface, accessibility, the duration of the sessions, the users' motivation and their expectations, among others. Moreover, an additional open-ended question was included to collect their personal suggestions for further improvements. It is noteworthy that optimal number of sequences and trained SWLDA models, previously computed in the calibration sessions for each subject, were used thereinafter in the online evaluation session.

4. Results

Results of the calibration sessions are depicted in Table 2, where training accuracies, optimal number of sequences, and percentage of error selections in control-state recordings are detailed for each user. As can be noticed, 4 MDS could not obtain training accuracies higher than 70%. Since 70% is usually considered as the minimal acceptable accuracy in the BCI literature, they were discarded from the subsequent assessment (Kübler et al., 2001; Kleih et al., 2010; Corralejo et al., 2014; Martínez-Cagigal et al., 2017a). Quantitative results of the evaluation sessions are shown in the Table 3, including the duration, the final accuracy and the OCM of each task. Moreover, their averages and the number of sequences of each user are also detailed. Questionnaire results are finally depicted in Table 4, which specifies the statements and the ranks provided by the users. Values range from 1 (i.e., totally disagree), to 7 (i.e., totally agree), where 4 means a neutral response. Note that positive and negative statements are alternated in order to reduce the acquiescence bias (Likert, 1932). With regard to the final open-ended question, two users demanded to get rid of the conductive gel, and one user demanded more speed.

5. Discussion

Four MDS were discarded from the assessment due to their low training accuracy (<70%) (Kübler et al., 2001; Kleih et al., 2010; Corralejo et al., 2014; Martínez-Cagigal et al., 2017a), probably because their P300 potentials were too attenuated or their latencies were too variable (Table 2). Since there are subjects with the same diseases that do not show this effect, the rationale behind it lies in indirect problems related to attention capability or gaze control. In particular, M01 exhibited lack of sustained attention capability; M07 suffered from essential tremors; M11 was unable to open his eyes properly; and M13 reported nystagmus, which causes involuntary eye movements, resulting in limited vision and lack of control over gaze. Fig. 4

Table 2: Calibration sessions results

User	**Classifier**		**Threshold**	
	TA	N_s	**A1**	**A2**
M01	67.0%	15	-	-
M02	89.0%	10	41.7%	83.3%
M03	92.0%	14	50.0%	50.0%
M04	100%	9	95.8%	95.8%
M05	100%	7	95.8%	70.8%
M06	100%	7	83.3%	77.8%
M07	8.0%	15	-	-
M08	100%	10	87.5%	68.2%
M09	100%	13	100%	72.2%
M10	100%	13	79.2%	79.2%
M11	57.0%	15	-	-
M12	100%	12	83.3%	87.5%
M13	56.0%	15	-	-
M14	100%	9	66.7%	58.3%
M15	100%	13	83.3%	87.5%
M16	100%	14	95.8%	87.5%
M17	89.0%	15	50.0%	33.3%
M18	100%	7	95.8%	91.7%
C01	100%	11	100%	91.7%
C02	100%	6	100%	97.2%
C03	100%	13	95.8%	95.8%
C04	100%	7	100%	95.8%
C05	100%	5	87.5%	91.7%
C06	100%	8	91.7%	91.7%
C07	100%	8	95.8%	100%
C08	100%	4	77.8%	91.7%
C09	100%	8	100%	100%
C10	100%	7	100%	95.8%

The prefix "M" stands for motor-disabled subjects, whereas "C" indicates the control subjects; "TA" stands for training accuracy; N_s indicates the number of sequences of each user; and "A1" and "A2" indicate the accuracy in the first and second threshold sessions, respectively.

depicts two sample ERPs recorded over channels Pz and Cz, one from M16, who could finish all tasks; and the other one from M07, who was discarded from the assessment. In contrast to the response of M16, the P300 potential of M07 is quite noisy and unrecognizable, which would explain the poor performance of his classifier in the training stage.

Table 3: Evaluation session results

User	Task 1 Dur.	Task 1 Acc.	Task 1 OCM	Task 2 Dur.	Task 2 Acc.	Task 2 OCM	Task 3 Dur.	Task 3 Acc.	Task 3 OCM	Task 4 Dur.	Task 4 Acc.	Task 4 OCM	Task 5 Dur.	Task 5 Acc.	Task 5 OCM	Task 6 Dur.	Task 6 Acc.	Task 6 OCM	N_s	Average accuracy	Average OCM
M02	01:52	66.7%	1.61	04:55	60.0%	2.04	06:09	66.7%	1.46	06:09	63.6%	1.79	08:59	63.6%	1.22	01:02	100%	1.94	10	65.2%	1.58
M03	03:06	100%	1.29	04:42	57.1%	1.49	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	14	72.7%	1.41
M04	01:05	100%	2.76	02:29	100%	2.42	04:36	100%	1.52	06:32	100%	1.68	09:12	77.8%	0.98	03:11	100%	1.57	9	95.1%	1.51
M05	01:05	100%	2.76	01:27	100%	2.76	03:35	85.7%	1.95	05:05	90.9%	2.16	04:31	100%	1.99	05:39	100%	1.94	7	95.6%	2.11
M06	01:33	100%	1.94	03:37	85.7%	1.94	03:04	100%	2.28	04:40	100%	2.36	05:31	100%	2.17	05:50	84.6%	2.23	7	94.3%	2.18
M08	01:33	100%	1.94	02:04	100%	1.94	05:07	85.7%	1.37	08:18	58.3%	1.45	03:29	40.0%	1.44	04:49	71.4%	1.45	10	71.1%	1.50
M09	02:01	100%	1.49	03:22	100%	1.49	06:39	100%	1.05	10:07	81.8%	1.09	05:35	50.0%	1.07	n.c.	n.c.	n.c.	13	84.4%	1.15
M10	02:01	66.7%	1.49	03:22	40.0%	1.49	07:43	75.0%	1.04	09:20	63.6%	1.18	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	13	63.0%	1.20
M12	01:52	66.7%	1.61	03:43	100%	1.61	07:07	75.0%	1.12	09:20	81.8%	1.18	11:02	60.0%	0.91	n.c.	n.c.	n.c.	12	76.3%	1.15
M14	01:05	66.7%	2.76	02:16	100%	1.76	05:38	85.7%	1.24	09:08	58.3%	1.31	06:26	66.7%	1.86	05:05	60.0%	1.97	9	68.8%	1.62
M15	02:01	100%	1.49	04:02	66.7%	1.49	07:02	87.5%	1.14	10:07	72.7%	1.09	11:58	100%	1.00	10:30	100%	1.05	13	88.2%	1.12
M16	02:10	66.7%	1.38	02:54	100%	1.38	07:75	75.0%	1.01	10:54	90.9%	1.01	12:53	91.7%	0.93	11:19	100%	0.97	14	89.8%	1.02
M17	02:20	100%	1.29	04:39	83.3%	1.29	10:08	66.7%	0.89	11:40	45.5%	0.94	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	15	65.5%	1.01
M18	01:05	100%	2.76	01:27	100%	2.76	03:35	100%	1.95	05:27	100%	2.02	06:26	100%	1.86	06:48	92.3%	1.91	7	98.0%	2.02
Mean	**01:46**	**88.1%**	**1.90**	**03:13**	**85.2%**	**1.85**	**06:01**	**84.8%**	**1.39**	**08:13**	**77.5%**	**1.48**	**07:31**	**77.2%**	**1.40**	**07:49**	**89.8%**	**1.67**	**10.93**	**80.6%**	**1.47**
SD	00:35	16.6%	0.60	01:09	20.7%	0.49	02:02	12.5%	0.43	02:22	18.4%	0.47	03:10	22.4%	0.48	03:15	14.9%	0.44	2.84	12.9%	0.40
C01	01:42	100%	1.76	02:16	100%	1.76	05:38	100%	1.24	07:47	90.9%	1.41	08:05	90.9%	1.30	09:12	91.7%	1.36	11	93.8%	1.38
C02	00:56	100%	3.23	01:14	100%	3.23	03:04	85.7%	2.28	04:40	100%	2.36	04:51	100%	2.17	05:31	100%	2.27	6	97.9%	2.37
C03	02:01	100%	1.49	04:02	83.3%	1.49	07:43	85.7%	0.908	10:07	100%	1.09	10:30	100%	1.00	13:01	92.3%	1.14	13	94.2%	1.10
C04	01:05	100%	2.76	02:10	66.7%	2.77	03:35	100%	1.95	05:27	81.8%	2.02	05:39	100%	1.55	09:43	73.3%	2.12	7	85.2%	1.95
C05	00:47	100%	3.87	01:02	100%	3.87	02:33	100%	2.74	03:54	90.9%	2.83	04:03	100%	2.61	04:36	100%	2.97	5	98.0%	2.90
C06	00:56	100%	4.30	01:14	100%	3.23	03:04	71.4%	2.28	06:14	100%	1.12	08:05	100%	1.30	09:12	66.7%	1.36	8	86.7%	1.57
C07	01:14	100%	2.42	02:04	60.0%	2.42	03:35	57.1%	1.95	05:27	81.8%	2.02	06:53	91.7%	1.50	07:22	81.8%	1.74	8	79.6%	1.84
C08	00:37	100%	4.84	00:50	100%	4.84	02:03	100%	3.42	03:07	100%	3.53	03:14	90.9%	3.26	03:41	91.7%	3.40	4	95.8%	3.55
C09	01:14	100%	2.42	01:39	100%	2.42	04:06	100%	1.71	06:38	91.7%	1.81	05:39	100%	1.86	06:26	100%	1.94	8	98.0%	1.90
C10	01:05	100%	2.76	01:49	80.0%	2.77	03:35	100%	1.95	05:27	100%	2.02	05:27	90.9%	1.86	06:26	91.7%	2.02	7	93.9%	2.06
Mean	**01:10**	**100%**	**2.99**	**01:50**	**89.0%**	**2.88**	**03:54**	**90.0%**	**2.04**	**05:53**	**93.7%**	**2.02**	**06:15**	**96.4%**	**1.84**	**07:31**	**89.0%**	**2.03**	**7.7**	**92.3%**	**2.06**
SD	00:25	0.0%	1.08	00:55	15.6%	0.98	01:39	15.1%	0.71	02:00	7.5%	0.76	02:10	4.6%	0.68	02:48	11.5%	0.72	2.7	6.3%	0.73

The prefix "M" stands for motor-disabled subjects, whereas "C" indicates the control subjects; "Dur." indicates the task duration; "Acc." indicates the task accuracy for each user; "OCM" stands for Output Characters per Minute; N_s indicates the number of sequences of each user; and "n.c." stands for "not completed", which means that the user could not finish the task and thus, durations, accuracies and OCM are not defined. Note that users M01, M07, M11 and M13 were discarded from the assessment because they could not obtain a minimum accuracy of 70% in the calibration sessions.

Unsurprisingly, quantitative results of the evaluation session (Table 3) show that CS obtained higher overall accuracies (92.3% $\pm$ 6.3%) than MDS (80.6% $\pm$ 12.9%). In fact, this difference in performance was demonstrated to be significant (Wilcoxon Signed-rank Test, p-value = 0.0375). Furthermore, the required number of sequences for CS was significantly lower (Wilcoxon Signed-rank Test, p-value = 0.0155) than for MDS, which used 7.7 $\pm$ 2.7 and 10.93 $\pm$ 2.84 sequences, respectively. Consequently, the bits per minute rate for CS (2.06 $\pm$ 0.73) was also higher than for MDS (1.47 $\pm$ 0.40), producing also significant differences (Wilcoxon Signed-rank Test, p-value = 0.0498). The less number of sequences, the higher output bits per minute. This assures a faster navigation through the application and thus, CS took less time than MDS to finish the tasks. These findings reinforce the necessity of assessing the reliability of BCI systems with end users.

With regard to the complexity of these tasks, the average durations of

Table 4: Questionnaire results

No.	**Statement**	**MDS**		**CS**	
		Mean	**SD**	**Mean**	**SD**
1	I found interesting to use the BCI social networking application	**6.07**	1.07	**6.00**	0.94
2	I found it difficult to control the system	**2.86**	1.79	**2.70**	1.34
3	My expectations for the application were completely met	**5.29**	1.64	**5.90**	0.99
4	I was bored during the assessment sessions	**2.14**	1.56	**3.50**	1.96
5	I found the assessment sessions entertaining	**5.57**	1.65	**4.80**	1.40
6	I can imagine myself using this BCI application in my daily life	**4.29**	2.34	**2.60**	1.84
7	It was stressful to concentrate when it was required	**3.00**	1.75	**2.60**	1.71
8	The application works smoothly	**4.71**	1.44	**5.80**	1.03
9	The duration of the calibration sessions was too long	**2.43**	1.74	**3.70**	1.89
10	User interface is intuitive and easy to understand	**4.79**	1.76	**5.70**	1.16
11	It takes much too long to control the BCI application	**4.14**	1.83	**4.20**	1.40
12	I would love to participate in other similar studies	**6.43**	0.76	**5.20**	1.62
13	I found it difficult to select the desired commands	**2.93**	1.90	**2.80**	1.23
14	I would gladly carry out more testing sessions with the BCI application	**6.00**	1.47	**4.80**	1.62
15	I did not find the flickering effect annoying	**4.07**	1.59	**5.10**	1.85
16	The duration of the evaluation session was too long	**2.14**	1.56	**3.60**	1.51
17	I would not need a manual for controlling Twitter and Telegram with this system	**4.93**	1.77	**5.90**	1.73
18	I am happy that the sessions are over	**4.07**	1.59	**4.90**	1.29
19	I think that this system could improve the social media accessibility	**5.86**	1.41	**6.40**	0.70
20	I became impatient during the sessions	**2.07**	1.69	**3.40**	1.51

Statements were ranked in a 7-point Likert scale, where 1 means a complete disagreement, 4 a neutral response, and 7 a complete agreement.

the Table 3 show a clear increase as the users advance through the tasks, especially for CS. However, the average accuracies for each of them does not show a constant decreasing, which could be expected at first glance. The first task was easily completed by all the participants (CS: 100% ± 0.0%; MDS: 88.1% ± 16.6%). The second task was also completed by all the participants, even though they reached lower accuracies (CS: 85.2% ± 20.7%; MDS: 89.0% ± 15.6%) and took three times more to finish than the first one. The third task was a struggle for M03, which could not finish it, probably because it was the first task that involved the use of both RCP matrices (CS: 90.0% ± 15.1%; MDS: 84.8% ± 12.5%). Like the previous one, the fourth task only was a problem for the same user, even though the duration increased appreciably (CS: 93.7% ± 7.5%; MDS: 77.5% ± 18.4%). The fifth task began

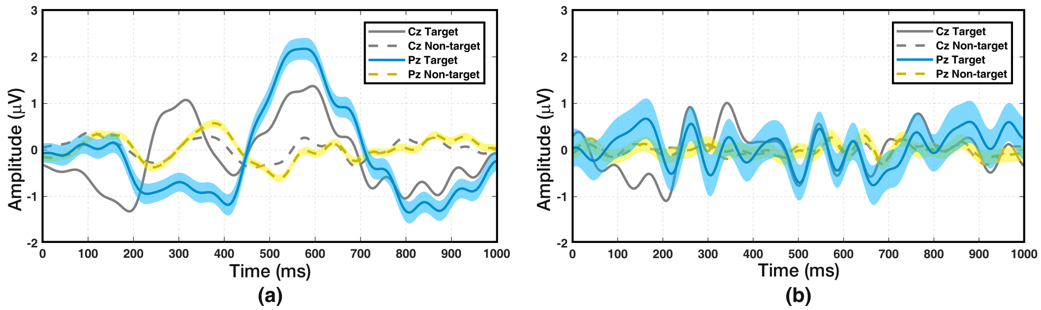

Figure 4: Event-related responses recorded in the first calibration session of two motor-disabled subjects: (a) M16, who could finish all tasks; and (b) M07, who was discarded due to its low classifier accuracy (<70%). Average curves of target stimuli (solid lines) and non-target stimuli (dashed lines) are depicted over the channel Pz (blue and yellow). Shaded areas indicate the 95% confidence interval of the aforementioned stimuli. Average curves over the channel Cz are also shown (grey). Note that a band-pass filter between 1–15 Hz has been applied for visualization purposes.

to be challenging, and three MDS were not able to complete it (CS: 96.4% ± 4.6%; MDS: 77.2% ± 22.4%). Finally, the sixth task was by far the most difficult one, causing that five MDS could not finish it (CS: 89.0% ± 11.5%; MDS: 89.8% ± 14.9%). Note that, despite of the highest presumed difficulty of the latter, MDS accuracies in the sixth task are higher than that obtained in the fifth one. This is because the metrics are only computed for the users that could finish the task, reducing the performance variability, as indicated by the standard deviation. As revealed above, although all CS were able to finish all tasks, there were several MDS who faced problems to finish them. In particular, the two most challenging tasks involved the use of both matrices and spelling long sentences in order to communicate via Telegram chats. It was observed that a selection error often causes more mistakes thereafter, probably due to despondency. This issue could be solved by integrating a spelling dictionary or processing error-related potentials (ErrP) (Schalk et al., 2000).

Concerning the qualitative analysis, questionnaire results show that participants were quite satisfied with the BCI application. All the positive statements were valued above the neutral response (i.e., 4), and all the negative statements but two were valued below it. These statements were the 11th, which concerns the required time to control the application; and the 18th, which means that some users were slightly happy that the assessment sessions were over. The former discloses a request to increase the speed of the system.

Nevertheless, the speed is directly related to the classifier performance, which depends on the user's calibration sessions. A more robust classifier, either because it would be based on a more sophisticated processing framework or because it would be trained with more data, could reach higher accuracies with fewer number of sequences, providing a faster navigation (Zhang et al., 2016). The latter reveals that the participation of several users implied an effort, a fact that should be taken into consideration when designing the tasks, their duration and the structure of the assessment sessions. However, users reported that they were willing to carry more sessions and to participate in further similar studies. Moreover, results show that these users did not experienced impatience, boredom, fatigue or stress. In addition, it is worthy to mention that the 6th statement was also valued below the neutral response for CS. This fact reveals that CS cannot imagine themselves using the BCI application in their daily life, which was expected because of their full physical and cognitive capabilities. Conversely, MDS do imagine themselves using the developed application as a daily tool, which reinforces the practicality of the system.

As pointed earlier, notwithstanding the growing popularity of smartphones, there are very few studies that have attempted to control their functionalities by integrating a BCI system. Table 5 shows these studies, which have been focused to dial numbers (Wang et al., 2011; Chi et al., 2012), accept incoming calls (Katona et al., 2014), call contacts (Campbell et al., 2010; Wang et al., 2011), play simple games (Wu et al., 2014), spell words (Obeidat et al., 2017; Elsawy et al., 2017) or open pre-installed apps and visualize the gallery (Elsawy and Eldawlatly, 2015). It is noteworthy that none of them has been focused on providing a high-level control of a smartphone, nor controlling social network functionalities. Moreover, the table 5 exposes one of the main drawbacks of the BCI literature, whose studies usually fail to prove the usability of their systems with end users. In fact, none of the aforementioned applications has been tested with motor-disabled users, who are the ones that would presumably benefit from them. It is also worthy to mention that none of these studies provides an asynchronous control, which implies that, in a real situation, an external supervisor should be present to pause the application when required. For this reason, one of the main objectives of this study is to evaluate our proposal with a population of 18 MDS in order to assess its usefulness to meet their daily communication needs.

Among the studies depicted in Table 5, P300 evoked potentials are the most prevalent control signals (Campbell et al., 2010; Elsawy and Eldawlatly,

Table 5: Comparison among state-of-the-art studies

Study	Control signal	EEG cap	Target SO	Processing	Main functionalities	N	Sub.	Accuracy[(1)]
Campbell et al. (2010)	P300	EPOC (Emotiv)	iOS	Mobile	Call contacts	3	CS	88.89%
Wang et al. (2011)	SSVEP	Custom headband	Cell phone	Computer	Dial numbers	10	CS	95.90%
Chi et al. (2012)	SSVEP	Custom dry electrode	Cell phone	Cell phone	Dial numbers	2	CS	89.00%
Katona et al. (2014)	Conc.	Mindset (Neurosky)	Windows phone	Headset	Accept/reject incoming calls	5	CS	75.00%
Wu et al. (2014)	Conc.	Mindset (Neurosky)	Android	Headset	Play a simple racing game	5	CS	-
Elsawy and Eldawlatly (2015)	P300	EPOC (Emotiv)	Android	Mobile	Open pre-installed apps and visualize the gallery	6 6	CS CS	79.17%[(2)] 87.5%
Elsawy et al. (2017)	P300	EPOC (Emotiv)	Android	Mobile	Spell words	6	CS	64.17%
Obeidat et al. (2017)	P300	EPOC (Emotiv)	Android	Mobile	Spell words	14	CS	90.00%
Present study	**P300**	**g.USBamp (g.Tec)**	**Android**	**Computer**	**Full asynchronous control of Twitter and Telegram**	**10** **18**	**CS** **MDS**	**92.30%** **80.60%**

"P300" refers to the P300 evoked potentials, "SSVEP" stands for steady-state visual evoked potentials, and "Conc." denotes a Neurosky concentration signal; "N" indicates the number of subjects; "CS" stands for control subjects, and "MDS" stands for motor-disabled subjects.
[(1)] Whether the study provides several accuracies for different experiments, the table shows the highest online reached performance. If accuracy is not provided directly, it is estimated from other data.
[(2)] The first accuracy belongs to the opening pre-intalled apps functionality, whereas the second one belongs to the visualizing application.

2015; Obeidat et al., 2017; Elsawy et al., 2017). However, the customized Neurosky concentration metric is also used as an endogenous control signal (Katona et al., 2014; Wu et al., 2014), and steady-state visual evoked potentials (SSVEP) as exogenous ones (Wang et al., 2011; Chi et al., 2012). Even though the signal processing of the former is simple and can be handled by the headset itself, the Neurosky concentration signal can only be used to make dichotomous decisions. In other words, the systems of Katona et al. (2014) and Wu et al. (2014) could only discriminate two different EEG states, hindering the use of this signal for providing a high-level control of a complex system, such as the smartphones. Regarding the latter, it is worthy to mention that the SSVEP-based studies were both focused to dial numbers in cell phones (Wang et al., 2011; Chi et al., 2012). SSVEP signals are based on a mimetic mechanism: when the retina is excited by a visual stimulus that flickers at a constant frequency, the brain generates an oscillatory response at the same frequency (Wolpaw et al., 2002; Pastor et al., 2003; Capilla et al., 2011; Luck, 2014). The main advantage of the SSVEP signal is its exogenous nature, which makes a training phase unnecessary. Moreover, the signal also provides high performances, as the results show (Wang et al., 2011; Chi et al., 2012). However, the most reliable flickering frequencies belongs to the low beta band (i.e., 13–19 Hz) (Volosyak et al., 2011), which maximize the risk of epileptic seizures and visual fatigue (Pastor et al., 2003). Furthermore, the standardization of vertical refresh rate of LCD screens also restricts the number of simultaneously displayed frequencies (Volosyak et al., 2009). Therefore, the number of possible commands is limited. With regard to the P300-based studies, the use of a wireless headset with saline electrodes allows them to integrate a simple signal processing stage in the final devices (i.e., iOS or Android). However, although this solution favors the users' comfort and the practicality of the system, it also sets up a trade-off between portability and performance. In fact, the CS average accuracy of our study (92.30%) is higher than the ones reported in all these previous approaches, probably due to the use of: (i) gel-based active electrodes, (ii) a more complex signal processing module, and (iii) a larger stimulation screen. Significant differences have been found between our study outcomes and the results of the opening apps system of Elsawy and Eldawlatly (2015) (Wilcoxon Signed-rank Test, p-value $= 0.0088$); and the mobile speller of Elsawy et al. (2017) (Wilcoxon Signed-rank Test, p-value $= 0.0007$). The remaining P300-based studies do not provide unfolded accuracy results for each user and thus, statistical analysis could not be performed. Furthermore, it is worthy to mention that no comparison with disabled subjects could have been made because of their lack of assessment with end users.

From the experimental outcomes, several insightful implications can be derived. On the one hand, this study may be considered as one of the first precursors of smartphone-based BCIs. As aforementioned, there are very few studies that have attempted to control mobile devices with BCI systems, and none of them was focused on providing a high-level control of a certain application. Our system provides a comprehensive control of two different social networks, covering all their functionalities and simultaneously reaching high accuracy results. To this end, users can select 72 different commands, arranged in two different RCP matrices. On the other hand, the present study has been tested with a population of both motor-disabled and control subjects and thus, the viability of the system has been demonstrated. Unfortunately, BCI-based studies usually fail to test their systems with real users, making it impossible to infer their reliability in a real context. Therefore, to the best of our knowledge, the present study is the first approach that has been proved its practicality to control a mobile BCI system by real users. These outcomes suggest that the developed system would be extended, in the near future, to assist individuals, companies or institutions that could be benefited from it. Consequently, personal autonomy and social integration of motor-disabled users could be improved, making an impact in their quality of life. To sum up, the main strengths of our proposal are:

i) Comprehensive control of Twitter and Telegram in Android platforms using brain signals.
ii) Ability to discriminate among a total of 72 different commands, arranged in two RCP matrices.
iii) Asynchronous control management by means of attention monitoring.
iv) Suitable performance accuracies.
v) Robustness, due to the evaluation with both control and motor-disabled populations.

Despite the results show that our BCI application allow users to successfully control Twitter and Telegram in an Android device, we can point out the following weaknesses:

i) Signal processing stage requires a laptop to be executed, which favors the reliability of the system, but impairs portability. Further research can overcome this limitation by using a wireless headset and integrating the processing stage into the final device.
ii) Asynchronous management is based on a wrapper method that depends on the LDA classifier and consequently, on the training performance of each user. Future endeavors must be focused on developing new asynchrony filter methods, such as SSVEP-based approaches independent of inter-session effects (Aloise et al., 2011; Pinegger et al., 2015; Wang et al., 2016; Jiao et al., 2017).
iii) Lack of despondency bypassing, causing a mistake to occasionally result in more errors in the following selections. A future research line could be aimed to implement a spelling dictionary or processing ErrPs to avoid extra selection errors (Cruz et al., 2018).
iv) Heterogeneous motor-disabled population. Although the application was tested with 18 MDS, and all of them can be considered end users of BCI systems, a future homogenization could be suitable for characterizing the performance of the system within a certain disease.

6. Conclusion

An asynchronous P300-based BCI system to control social networking applications of smartphones or tablets has been designed, developed and tested with both healthy and motor-disabled users. The system monitors the EEG signal of the user, while a RCP matrix containing the application commands flashes its rows and columns in order to generate P300 evoked potentials on the user's scalp. The selected commands are sent in real-time to the final Android device via Bluetooth, which interprets them and provides visual feedback to the user. The system has been tested with 10 CS and 18 MDS. The assessment was composed of two calibration stages and one evaluation session, where the users had to complete 6 different tasks, sorted by difficulty. Both quantitative and qualitative metrics were obtained, reaching average accuracies of 92.3% for CS and 80.6% for MDS. To the best of our knowledge, this is the first BCI study aimed to control social networking applications in a comprehensive way. Significant differences have been found among our accuracy results and that reported in other related studies, which obtained lower performances. Therefore, our P300-based BCI socializing system proves to be a suitable solution for motor-disabled users, allowing them to meet their daily communication needs.

In spite of the positive results, future research work can be suggested. Future endeavors should be aimed to: (i) embed the signal processing stage in the final device, (ii) design an asynchronous management independent of the classifier, (iii) implement a dictionary that suggests common words to the users based on their previous selections, (iv) process ErrPs to identify prediction errors and avoid wrong selections in real-time, and (v) test the application with a homogenized disabled population in order to study the performance within a certain disease.

Acknowledgments

This study was partially funded by projects TEC2014-53196-R and DPI2017-84280-R of 'Ministerio of Economía y Competitividad' and FEDER, the project "Análisis y correlación entre el genoma completo y la actividad cerebral para la ayuda en el diagnóstico de la enfermedad de Alzheimer" (Inter-regional cooperation program VA Spain-Portugal POCTEP 2014-202) of the European Commission and FEDER, and project VA037U16 of the 'Junta de Castilla y León' and FEDER. V. Martínez-Cagigal and J. Gomez-Pilar were in receipt of a PIF-UVa grant of the University of Valladolid.

Declaration of interest

The authors declare no conflict of interest.

References

References

Aloise, F., Schettini, F., Aricò, P., Leotta, F., Salinari, S., Mattia, D., Babiloni, F., Cincotti, F., 2011. P300-based brain–computer interface for environmental control: an asynchronous approach. J. Neural Eng. 8 (2), 25025.

Atkinson, J., Campos, D., 2016. Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers. Expert Systems with Applications 47, 35–41.
URL `http://dx.doi.org/10.1016/j.eswa.2015.10.049`

Blankertz, B., Lemm, S., Treder, M., Haufe, S., Müller, K. R., 2011. Single-trial analysis and classification of ERP components - A tutorial. NeuroImage 56 (2), 814–825.
URL `http://dx.doi.org/10.1016/j.neuroimage.2010.06.048`

Blondet, M. V. R., Badarinath, A., Khanna, C., Jin, Z., 2013. A wearable real-time BCI system based on mobile cloud computing. International IEEE/EMBS Conference on Neural Engineering, NER, 739–742.

Campbell, A., Choudhury, T., Hu, S., Lu, H., Mukerjee, M. K., Rabbi, M., Raizada, R. D. S., 2010. NeuroPhone: brain-mobile phone interface using a wireless EEG headset. Proceedings of the Second ACM SIGCOMM workshop on Networking, systems, and applications on mobile handhelds (MobiHeld'10), 3–8.

Capilla, A., Pazo-Alvarez, P., Darriba, A., Campo, P., Gross, J., 2011. Steady-state visual evoked potentials can be explained by temporal superposition of transient event-related responses. PLoS ONE 6 (1).

Chen, L.-L., Zhao, Y., Ye, P.-F., Zhang, J., Zou, J.-Z., 2017. Detecting driving stress in physiological signals based on multimodal feature analysis and kernel classifiers. Expert Systems with Applications 85, 279–291.
URL `http://dx.doi.org/10.1016/j.eswa.2017.01.040`

Chi, Y. M., Wang, Y. T., Wang, Y., Maier, C., Jung, T. P., Cauwenberghs, G., 2012. Dry and noncontact EEG sensors for mobile brain-computer interfaces. IEEE Trans. Neural Syst. Rehabil. Eng. 20 (2), 228–235.

Corralejo, R., Nicolás-Alonso, L. F., Álvarez, D., Hornero, R., 2014. A P300-based brain–computer interface aimed at operating electronic devices at home for severely disabled people. Med. Biol. Eng. Comput. 52 (10), 861–872.

Cruz, A., Pires, G., Nunes, U. J., 2018. Double ErrP Detection for Automatic Error Correction in an ERP-Based BCI Speller. IEEE Transactions on Neural Systems and Rehabilitation Engineering 26 (1), 26–36.

Da Silveira, T. L., Kozakevicius, A. J., Rodrigues, C. R., 2016. Automated drowsiness detection through wavelet packet analysis of a single EEG channel. Expert Systems with Applications 55, 559–565.
URL http://dx.doi.org/10.1016/j.eswa.2016.02.041

Elsawy, A. S., Eldawlatly, S., 2015. P300-based applications for interacting with smart mobile devices. In: 7th Annual International IEEE EMBS Conference on Neural Engineering. pp. 166–169.

Elsawy, A. S., Eldawlatly, S., Taher, M., Aly, G. M., 2017. MindEdit: a P300-based text editor for mobile devices. Comput. Biol. Med. 80 (August 2016), 97–106.

Farwell, L. A., Donchin, E., 1988. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr. Clin. Neurophysiol. 70 (6), 510–523.

Hill, N. J., Wolpaw, J. R., 2016. Brain–Computer Interface. In: Reference Module in Biomedical Sciences. Elsevier.
URL http://www.sciencedirect.com/science/article/pii/B978012801238399322X

International Data Corporation, 2017. IDC quarterly mobile phone tracker. Tech. rep.
URL https://www.idc.com/tracker

Ipsos MORI, Google, 2017. Something for everyone: why the growth of mobile apps is good news for brands. Tech. rep.

Jasper, H. H., 1958. The ten twenty electrode system of the international federation. Electroencephalography and clinical neurophysiology 10, 371–375.

Jayabhavani, G. N., Raajan, N. R., Rubini, R., 2013. Brain mobile interfacing (BMI) system embedded with wheelchair. 2013 IEEE Conference on Information and Communication Technologies, ICT 2013 (Ict), 1129–1133.

Jiao, Y., Zhang, Y., Wang, Y., 2017. A Novel Multilayer Correlation Maximization Model for Improving CCA-Based Frequency Recognition in SSVEP Brain – Computer Interface. International Journal of Neural Systems 27 (8), 1–14.

Katona, J., Peter, D., Ujbanyi, T., Kovari, A., 2014. Control of incoming calls by a Windows Phone based Brain Computer Interface. 15th IEEE International Symposium on Computational Intelligence and Informatics (CINTI 2014), 121–125.

Keinosuke, F., 1990. Introduction to statistical pattern recognition. Academic Press Inc.

Kemp, S., 2017. Digital in 2017: global overview. Tech. rep.

Kleih, S. C., Nijboer, F., Halder, S., Kübler, A., 2010. Motivation modulates the P300 amplitude during brain-computer interface use. Clin. Neurophysiol. 121 (7), 1023–1031.

Krusienski, D. J., Sellers, E. W., Cabestaing, F., Bayoudh, S., McFarland, D. J., Vaughan, T. M., Wolpaw, J. R., 2006. A comparison of classification techniques for the P300 Speller. J. Neural Eng. 3 (4), 299–305.

Krusienski, D. J., Sellers, E. W., McFarland, D. J., Vaughan, T. M., Wolpaw, J. R., 2008. Toward enhanced P300 speller performance. J. Neurosci. Methods 167 (1), 15–21.

Kübler, A., Birbaumer, N., 2008. Brain-computer interfaces and communication in paralysis: Extinction of goal directed thinking in completely paralysed patients? Clin. Neurophysiol. 119 (11), 2658–2666.

Kübler, A., Kotchoubey, B., Kaiser, J., Birbaumer, N., Wolpaw, J. R., 2001. Brain-computer communication: Unlocking the locked in. Psychol. Bull. 127 (3), 358–375.

Kübler, A., Nijboer, F., Birbaumer, N., 2007. Brain-Computer Interfaces for communication and motor control – perspectives on clinical application. In: Toward Brain-Computer Interfacing, 1st Edition. MA: The MIT Press, pp. 373–391.

Likert, R., 1932. A technique for the measurement of attitudes. Arch. Psychol.

Luck, S. J., 2014. An introduction to the event-related potential technique. MIT press.

Ma, J., Zhang, Y., Cichocki, A., Matsuno, F., 2015. A novel EOG/EEG hybrid human-machine interface adopting eye movements and ERPs: Application to robot control. IEEE Transactions on Biomedical Engineering 62 (3), 876–889.

Martínez-Cagigal, V., Gomez-Pilar, J., Álvarez, D., Hornero, R., 2017a. An asynchronous P300-based Brain-Computer Interface web browser for severely disabled people. IEEE Trans. Neural Syst. Rehabil. Eng. 25 (8), 1332–1342.

Martínez-Cagigal, V., Hornero, R., 2017. P300-based Brain-Computer Interface channel selection using swarm intelligence. Rev. Iberoam. Autom. In. 14 (4), 372–383.

Martínez-Cagigal, V., Núñez, P., Hornero, R., 2017b. Spectral Regression Kernel Discriminant Analysis for P300 Speller Based Brain-Computer Interfaces. In: Converging Clinical and Engineering Research on Neurorehabilitation II. Biosystems & Biorobotics. Springer, Segovia, Spain, pp. 789–793.

Narsky, I., Porter, F. C., 2013. Statistical analysis techniques in particle physics: fits, density estimation and supervised learning. John Wiley & Sons.

Obeidat, Q., Campbell, T., Kong, J., 2017. Spelling with a small mobile Brain-Computer Interface in a moving wheelchair. IEEE Trans. Neural Syst. Rehabil. Eng. 4320 (c), 1.

Pastor, M. A., Artieda, J., Arbizu, J., Valencia, M., Masdeu, J. C., 2003. Human cerebral activation during steady-state visual-evoked responses. J. Neurosci. 23 (37), 11621–11627.

Picton, T. W., 1992. The P300 wave of the human event-related potential. J. Clin. Neurophysiol. 9 (4), 456–479.

Pinegger, A., Faller, J., Halder, S., Wriessnegger, S. C., Müller-Putz, G. R., 2015. Control or non-control state: that is the question! An asynchronous visual P300-based BCI approach. J. Neural Eng. 12 (1), 14001.

Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., Wolpaw, J. R., 2004. BCI2000: A general-purpose brain-computer interface (BCI) system. IEEE Trans Biomed. Eng. 51 (6), 1034–1043.

Schalk, G., Wolpaw, J. R., McFarland, D. J., Pfurtscheller, G., 2000. EEG-based communication: presence of an error potential. Clin. Neurophysiol. 111 (12), 2138–2144.

Sellers, E. W., Donchin, E., 2006. A P300-based brain-computer interface: initial tests by ALS patients. Clin. Neurophysiol. 117 (3), 538–548.

Speier, W., Arnold, C., Pouratian, N., 2013. Evaluating true BCI communication rate through mutual information and language models. PLoS ONE 8 (10).

Townsend, G., LaPallo, B. K., Boulay, C. B., Krusienski, D. J., Frye, G. E., Hauser, C. K., Schwartz, N. E., Vaughan, T. M., Wolpaw, J. R., Sellers, E. W., 2010. A novel P300-based brain-computer interface stimulus presentation paradigm: moving beyond rows and columns. Clin. Neurophysiol. 121 (7), 1109–1120.

Volosyak, I., Cecotti, H., Gräser, A., 2009. Optimal visual stimuli on LCD screens for SSVEP based brain-computer interfaces. 2009 4th International IEEE/EMBS Conference on Neural Engineering, NER '09, 447–450.

Volosyak, I., Valbuena, D., Lüth, T., Malechka, T., Gräser, A., 2011. BCI demographics II: how many (and what kinds of) people can use a high-frequency SSVEP BCI? IEEE Trans. Neural Syst. Rehabil. Eng. 19 (3), 232–239.

Wang, H., Zhang, Y., Waytowich, N. R., Krusienski, D. J., Zhou, G., Jin, J., Wang, X., Cichocki, A., 2016. Discriminative Feature Extraction via Multivariate Linear Regression for SSVEP-Based BCI. IEEE Transactions on Neural Systems and Rehabilitation Engineering 24 (5), 532–541.

Wang, Y.-T., Wang, Y., Jung, T.-P., 2011. A cell-phone-based brain-computer interface for communication in daily life. J. Neural Eng. 8, 25018.

Wolpaw, J. R., Birbaumer, N., Heetderks, W. J., McFarland, D. J., Peckham, P. H., Schalk, G., Donchin, E., Quatrano, L. A., Robinson, C. J., Vaughan, T. M., 2000. Brain-computer interface technology: a review of the first international meeting. IEEE Trans. Rehabil. Eng. 8 (2), 164–173.

Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., Vaughan, T. M., 2002. Brain-computer interfaces for communication and control. Clinical Neurophysiology 113 (6), 767–91.

World Health Organization, 2011. World report on disability. Tech. rep., World Health Organization, Switzerland.

Wu, G., Xie, Z., Wang, X., 2014. Development of a mind-controlled Android racing game using a brain computer interface (BCI). 2014 4th IEEE International Conference on Information Science and Technology, 652–655.

Yuan, P., Gao, X., Allison, B., Wang, Y., Bin, G., Gao, S., 2013. A study of the existing problems of estimating the information transfer rate in online brain-computer interfaces. Journal of Neural Engineering 10 (2).

Zammouri, A., Ait Moussa, A., Mebrouk, Y., 2018. Brain-computer interface for workload estimation: Assessment of mental efforts in learning processes. Expert Systems with Applications 112, 138–147.
URL https://doi.org/10.1016/j.eswa.2018.06.027

Zhang, Y., Zhou, G., Jin, J., Zhao, Q., Wang, X., Cichocki, A., 2016. Sparse Bayesian Classification of EEG for Brain-Computer Interface. IEEE Transactions on Neural Networks and Learning Systems 27 (11), 2256–2267.