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A P300-based brain-computer interface aimed at operating electronic devices at home for severely disabled people

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The present study aims at developing and assessing an assistive tool for operating electronic devices at home by means of a P300-based brain-computer interface (BCI). Fifteen severely impaired subjects participated in the study. The developed tool allows users to interact with their usual environment fulfilling their main needs. It allows for navigation through 10 menus and to manage up to 113 control commands from 8 electronic devices. Ten out of the fifteen subjects were able to operate the proposed tool with accuracy above 77%. Eight out of them reached accuracies higher than 95%. Moreover, bitrates up to 20.1 bit/min were achieved. The novelty of this study lies in the use of an environment control application in a real scenario: real devices managed by potential BCI end-users. Although impaired users might not be able to set up this system without aid of others, this study takes a significant step to evaluate the degree to which such populations could eventually operate a stand-alone system. Our results suggest that neither the type nor the degree of disability is a relevant issue to suitably operate a P300-based BCI. Hence, it could be useful to assist disabled people at home improving their personal autonomy.

Brain-computer interfaces, electroencephalography, P300 event-related potentials, people with disabilities, communication aids for disabled

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1. Introduction

Brain-computer interfaces (BCIs) allow users to communicate with others and control the external world without using the conventional neuromuscular pathways of peripheral nerves and muscles [22, 41]. Brain activity is monitored and specific signal features reflecting the user's intent are extracted and translated into a command that operates a device [41]. Thus, users are able to communicate and control their environment. Hence, BCIs would allow to restore the communication and the control ability of people with severe motor disabilities [24]. The group of potential end-users include individuals who are severely disabled by disorders such as stroke, spinal-cord injuries, amyotrophic lateral sclerosis (ALS), cerebral palsy and other serious neuromuscular diseases or injuries [22].

Electroencephalogram (EEG) is commonly used to record brain activity in non-invasive BCIs. EEG is a portable technique and it requires relatively simple and inexpensive equipment [41]. According to the nature of input signals, BCIs can be classified into two groups. Endogenous BCIs depend on user control of electrophysiological activity originated internally, such as amplitude in a specific frequency band in EEG recorded over a specific cortical area [42]. BCIs based on motor imagery or slow cortical potentials are endogenous systems and often require extensive training [42]. On the other hand, exogenous BCIs depend on electrophysiological activity originated externally, i.e., evoked by specific stimuli. They may not require extensive training but they require a slightly structured environment [42]. Due to standard visual stimuli needed to elicit this exogenous activity may depend to some degree on control of eye gaze [41], locked-in patients or subjects with poor control of eye movements might achieve better communication when tactile feedback is used [42]. BCIs based on P300 potentials or steady-state visual evoked potentials are exogenous systems. Our study is focused on P300-based BCIs.

P300 response is an event-related potential (ERP) evoked in EEG over parietal cortex. It is a typical, or naive, response to a desired choice [5]. Infrequent or particularly significant auditory, visual or somatosensory stimuli, when

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interspersed with frequent or routine stimuli, typically evoke in EEG a positive peak at about 300 ms [41]. P300-based BCIs allow to select among several items displayed in the screen using this 'oddball' response [6, 8, 41]. The stimuli matrix shows an array with the different items in the screen. Usually, each stimulus consists in the flashing of a single row or column of this matrix. When the user's desired item flashes, an evoked potential response appears in the subject's EEG activity. Previous studies focused on improving P300-based BCIs performance assessing feature extraction and classification methods [2, 17, 19, 31, 32, 39, 43] or different visual stimuli presentation paradigms [15, 16, 33, 38]. Other studies focused on developing novel BCI applications [13, 25, 26]. Nevertheless, most BCI studies are performed with young healthy adults instead of severely impaired people who are the potential end-users [23]. Few studies verified the usefulness of P300-based BCIs for severely disabled people [3, 10, 24, 28, 29, 37, 40]. Furthermore, these studies use just one stimuli matrix with a reduced number of options and allowing limited interaction.

The present study aims at developing and assessing a P300-based BCI tool to assist severely disabled people at home. The proposed BCI application will allow users to operate electronic devices fulfilling their main comfort, entertainment and communication needs. The assistive BCI tool applies stepwise linear discriminant analysis (SWLDA) in order to select the most significant features for each user. A population of severely impaired subjects will interact with the proposed tool, assessing its performance and usefulness for increasing their personal autonomy at home.

The novelty of this study lies in the use of an environment control application in a real scenario: real devices, usually present at home, operated by end-users. Fifteen subjects with different pathologies and degrees of disability took part in the study. Most of them presented both motor and cognitive impairments. If we compare to previous works [3, 10, 24, 28, 29, 37, 40], in our study a large population of potential BCI end-users interacted with the proposed assistive tool in their usual environment.

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2. Methods

2.1 Subjects and signals

Fifteen individuals (mean age: 50.27 years; range: 35-68 years; 7 males, 8 females) with different pathologies and motor impairments were included in this study. All participants were patients from the Spanish National Reference Centre on Disability and Dependence, located in León (Spain). All subjects were BCI-naives (without any P300-based BCI previous experience). Table 1 summarizes the clinical data of all participants. Despite of his severe diagnosis, participant P1 did not show motor impairments at the time of the study. The study was approved by the local ethics committee. All subjects gave their informed consent for participation in the study. To the best of our knowledge, this is the first study over a large population consisted of people with different degree of both motor and cognitive impairments caused by different pathologies.

INSERT TABLE 1 AROUND HERE

EEG was recorded with 8 active electrodes from channels: Fz, Cz, P3, Pz, P4, PO7, PO8 and Oz, according to the modified international 10-20 system [14]. Figure 1 a) shows the EEG recording montage. Recordings were referenced to the right earlobe and grounded to channel Fpz. EEG data was amplified with a g.USBamp biosignal amplifier (Guger Technologies OG, Graz, Austria), sampled at 256 Hz and bandpass filtered at 0.1-60 Hz. Common Average Reference (CAR) was used as spatial filter and a notch filter at 50 Hz was applied in order to remove the power line interference. Data collection and design of experiments were controlled by BCI2000, a general-purpose BCI software platform [34, 35].

INSERT FIGURE 1 AROUND HERE

2.2 EEG signal processing

2.2.1 Classifier design

The waveforms of the EEG recorded signals were used as features. Figure 1 c) presents a typical waveform of the P300 response. Segments of 800 ms

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immediately after each stimulus were extracted and averaged for each EEG channel, since P300 evoked potentials appear about 300 ms after the stimulus [41]. Then, signals were filtered employing a moving average (MA) filter implemented as "Direct form II Transposed". It works as a low pass filter to remove high frequency components of the signal [35]. Afterwards, because of the high sampling rate of the EEG recordings relative to the low frequency of the P300 evoked responses [12, 20], data was downsampled to 20 Hz [19, 20]. In order to compose the classifier, SWLDA was applied. SWLDA selects suitable features to be included in a multiple regression model [20]. For binary classification tasks, such as identifying if a stimulus elicited an ERP or not, the linear discriminant and least-squares regression solutions are equivalent [35]. A combination of forward and backward stepwise selection was applied. The stepwise method decides to add or to remove a feature from the model by means of an iterative process. It selects the strongest features from the feature set and removes the features that provide redundant information in terms of statistical significant differences associated to the *F*-test [7, 35]. At the first step, the most important feature, i.e.: the one with the smallest *p*-value from the statistical *F*-test, is added to the model if its associated *p*-value is less than a significance level p_{in}. At the second step, to determine whether any of the remaining variables are important once this feature is in the model, the algorithm searches for statistical differences between the present model and every new model composed of the current feature and one of the remaining variables. The single feature with the smallest *p*-value is added to the model is its associated *p*-value is less than p_{in}. It is possible that the previously selected feature is no longer important once the current variable has been added to the model. Thus, the third step performs a check for backward elimination [11, 37]. This is accomplished by fitting models that delete one of the features added in the previous steps and assessing the importance of the variable removed. To determine whether a feature should be deleted from the model the algorithm selects that variable which, when removed, yields the maximum *p*-value. If the maximum *p*-value to remove exceeds the significance level p_{out} then the associated feature is removed from the model. Otherwise, the variable remains in the model. Subsequently, the method proceeds to the forward selection phase. The process continues in this manner until one of these conditions is fulfilled: (i) all features in the model have *p*-values lower than

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p_{out} and the remaining features have p-values greater than p_{in} or (ii) the model reaches a maximum predetermined number of features [11, 35]. A full description of the stepwise regression algorithm may be found in [7]. SWLDA performs feature space reduction by selecting suitable spatiotemporal features (i.e., the amplitude value at a particular time sample and channel location) to be included in a discriminant function based on the features with the greatest unique variance [19, 28]. In this study, the discriminant function was restricted to contain a maximum of 60 features [2, 18, 19, 20, 28, 35] and it was derived by using p_{in} = 0.1 and p_{out} = 0.15, commonly applied in P300-based BCI studies [19, 20, 35, 37, 38]. The selected spatiotemporal features compose the specific classifier for each subject.

2.2.2 Online processing

The classifier built using SWLDA was applied during the evaluation sessions. The temporal average of the waveform responses for each stimulus is computed for each channel. Then, the spatiotemporal features that compose the classifier are combined into a single value. Under the assumption that noise is Gaussian distributed with equal covariance for both classes, this value represents the likelihood for each response to be an ERP [35]. This study proposes a row/column stimuli pattern. Thus, the item in the intersection of the row and column with the greatest response values will be considered the desired target.

2.3 Assistive BCI tool for operating electronic devices at home

In this study, a P300-based BCI tool for managing electronic devices at home was developed. Our assistive BCI application allows users to control 8 devices related to comfort, communication and entertainment needs. Specifically, the developed assistive tool manages the following devices and their main functionalities:

- Television (TV). Switch on/off, volume control, switch TV channels: up/down or select from 0 to 9 and access and navigate through the configuration menu and the electronic program guide (EPG) service.

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- DVD player. Switch on/off, play, pause or stop a video, explore contents, switch to the next or previous file, mute and record the actual channel.
- Hi-Fi system. Switch on/off, volume control, change to radio or CD function, play, pause or stop a track and switch to the next or previous track or radio station.
- Multimedia hard drive. Switch on/off, explore hard drive's contents, play, pause, stop or switch to the next or previous file and show or hide subtitles.
- Lights. Switch on/off, change the light colour, turn up/down the light intensity and enable the flashing mode.
- Heater. Switch on/off, turn up/down power intensity, program the sleep function from 30 min to 4 hours and enable or disable the swing mode.
- Fan. Switch on/off, increase or decrease speed, program the sleep function, and enable or disable a specific internal fan or the swing mode.
- Phone. Pick up or hang up the phone, dial a phone number, automatically dial the emergency phone number or a previously memorized phone number and redial the last phone number.

All devices are operated by means of an infrared (IR) emitter device (RedRat Ltd., Cambridge, UK) connected to the computer. Our application uses the RedRat Software Development Kit (SDK) for storing and sending the control commands of each device.

The proposed tool is based on the P3Speller application from BCI2000 [34, 35]. Our application shows pictures of electronic devices and their commands instead of characters. Moreover, dimming instead of flashing stimuli are used since it was experimentally proved that stimuli are more prominent and users reported that visual annoyance is reduced for our specific pictures. Initially, the main menu of the assistive BCI tool is presented. As shown in figure 2, it consists in a 3 x 4 matrix of pictures. Each item in the first two rows of the matrix depicts one device: TV, DVD player, Hi-Fi system, multimedia drive, lights, heater, fan and phone. The last row shows the phone book and three application control commands: pause, resume and stop. According to the typical P300 paradigm [6], 15 sequences of random dimming stimuli are presented for each item selection. Each sequence contains one stimulus for each row and one for each column (i.e.,

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7 stimuli for the main menu). Stimuli occur randomly every 187.5 ms: each stimulus dims for 62.5 ms and then the screen remains unvarying for 125 ms [9, 18, 40]. Users are asked to attend to a specific item from the matrix and count how many times it dims. Once the matrix finishes flickering, auditory feedback is given and the selected command is performed: accessing a specific submenu, pause, resume or stop the application. Thus, users can access to several submenus for managing a specific device from the main menu. Submenus are implemented by means of variable size matrices, consisted of images depicting different functions of each device and the option of returning to the main menu. Size of submenus matrices are 3 x 4, 4 x 4 or 5 x 5, depending on the functionalities of each specific device. Figure 3 shows the TV and phone submenus, respectively. Likewise to the main menu, rows and columns of the submenu matrix are randomly dimmed. Users are asked again to focus on the item depicting the desired command and silently count how many times it dims. Once the system identifies the desired option, auditory feedback is given and the appropriate control command is performed (e.g., switch on the heater or mute the TV sound). Then, a pause of 6 s is set. This long pause is set in order to satisfy two requirements. Firstly, users are able to check if the desired command was properly performed or the desired menu was accessed. Secondly, users can also locate the next required item within the matrix. Therefore, users can navigate through the developed tool by means of multiple menus and operate eight electronic devices, which are usually present at home.

INSERT FIGURE 2 AROUND HERE

INSERT FIGURE 3 AROUND HERE

2.4 Procedure

Participants were seated in a comfortable chair or in their own wheelchair facing a computer flat screen, as shown in figure 1 b). Each subject was intended to perform three sessions: one session for calibration tasks and two evaluation sessions for assessing the BCI tool (Eval1 and Eval2).

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The Calibration session was comprised of 10 runs of approximately 4 min each. Data was collected in copy-spelling mode [20, 38]. In this initial session, only one matrix was presented to the user: the 5 x 5 TV submenu matrix. In each run, the user was asked to focus on a specific item from a proposed series of 5-6 items. 15 sequences of stimuli were presented for each single item selection. Runs were separated by intervals of 60 s. This session approximately lasted one hour. During the Calibration session, feedback was not provided to participants. Similarly to the protocol performed by Mak *et al* [24], SWLDA was applied to data from the 5 first runs of the Calibration session to determine the classifier weights for each user. This classifier was used during the subsequent 5 runs of the Calibration session.

Eval1 started with 12 items of copy-spelling using the TV submenu matrix in order to ensure proper performance [28]. Subsequently, participants were ready to interact with the proposed assistive BCI tool and all available submenus. Eval1 session comprised at least 7 evaluation runs. In each run, participants were asked to select items across different menus in order to complete a proposed series of at least 6 items, e.g.: “access the TV menu”, “switch to channel 8”, “turn up the volume”, “return to the main menu”, “access the DVD menu”, “record the actual channel”. For each single item selection, 15 sequences of stimuli were presented during Eval1. For each subject, the classifier built during the previous Calibration session was applied during the running of Eval1 and Eval2, unless during the initial copy-spelling items of Eval 1 an improper performance was detected. In this specific case, a new classifier was created using these initial copy-spelling runs.

Eval2 session was similar to Eval1. Participants started with 12 items of copy-spelling facing the TV submenu matrix in order to ensure proper performance [28]. Then, subjects were asked to select items across different menus in order to complete previously proposed tasks. During Eval2, the number of sequences of stimuli was reduced for each user in order to decrease the selection time. The less the number of sequences needed to suitably detect the P300 peak, the faster the users can navigate through all devices and control commands. Recordings from previous sessions were analysed offline providing accuracy as a function of the

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number of sequences. Then, the minimum number of sequences that allowed to correctly identify all targets was assigned for each participant to perform Eval2 session. The lowest number of sequences assigned was 3, corresponding to the participants with the highest offline performance (P2, P4 and P12). This methodology allows us to measure the maximum information transfer rate (ITR) achieved per subject.

Since a level of 70% is regarded as the minimum level of communication accuracy [18, 21], subjects were required to achieve minimum success (accuracy above 70%) either over the last runs of the Calibration session or over the first copy-spelling runs of the subsequent session. Participants who did not meet this requirement repeated the Calibration tasks during the next session. Moreover, participants who did not reach online accuracy rates higher than 70% during Eval1 session repeated the Eval1 tasks during the next session.

Finally, after having completed three sessions, the participants evaluated the assistive BCI tool by means of a custom questionnaire [1, 27]. The questionnaire consisted of 10 statements. Users had to assess the design, interface, usability and usefulness of the BCI tool rating each statement on a 5-point Likert scale (0-strongly disagree, 1-disagree, 2-neutral, 3-agree, 4-strongly agree). Odd statements were positive assertions about the assistive BCI tool (ideal score: 4) while even statements were negative assertions (ideal score: 0).

Results were measured in terms of online accuracy (ACC) for each kind of session, percentage of finished tasks (FT), maximum selection rate (SR) and ITR. Online accuracy of the Calibration session was measured by means of the classifier built using the 5 first runs. Then, this classifier was applied over the subsequent runs of this session. For the evaluation sessions (Eval1 and Eval2), ACC was measured as the percentage of items accurately classified according to the previously proposed tasks. The percentage of finished tasks indicates how many tasks the users were able to complete through Eval2 session (i.e., the percentage of runs they were able to finish all proposed item selections: “access the TV menu”, “switch to channel 8”, “turn up the volume”, “return to the main menu”, “access the DVD menu”, and “record the actual channel”). Moreover, the

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maximum SR (item/min) and ITR (bit/min) achieved by each user during the last evaluation session were calculated.

3 Results

The results achieved by all participants in the study are summarized in Table 2. Furthermore, figure 4 shows the online performance reached by each subject across sessions. Regarding the Calibration session results, thirteen out of the fifteen participants were able to reach online accuracy above 65% during this session. Seven out of them achieved accuracies higher than 90%, as shown in figure 4. Subject P11 had to repeat the Calibration session because she did not understand appropriately the task during the first session. However, she was able to achieve 80% accuracy in the next Calibration session. Only participant P13 could not interact with the BCI tool. During the first Calibration session, it was not possible to derive a reliable classifier for this user. Thus, he repeated the Calibration tasks during the subsequent session.

INSERT TABLE 2 AROUND HERE

INSERT FIGURE 4 AROUND HERE

In regard to the results of the evaluation sessions, ten out of the fourteen participants were able to control the developed BCI application with accuracies above 75%. Eight out of them even reached accuracies higher than 95%. As indicated in figure 4, these eight users also achieved high accuracy during Eval2 session, when less sequences of stimuli were presented. Furthermore, they completed all proposed tasks during Eval2 runs, i.e., they reached 100% FT. The remaining participants (P5, P6, P11 and P15) achieved accuracy lower than 65% during Eval1 session. Three out of them repeated Eval1 tasks during the next session and all of them, except P5, improved their accuracy results. Finally, in terms of SR and ITR, subjects that achieved high accuracies during the evaluation sessions were able to operate the assistive tool with fewer sequences of stimuli

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and thus with higher bitrates. SR ranged from 2.23 up to 5.89 item/min and ITR ranged from 2.19 up to 20.1 bit/min with the pause between selections; while SR ranged from 2.87 up to 14.33 item/min and ITR ranged from 2.82 up to 48.80 bit/min without the pause between selections.

Participants completed an assessment questionnaire immediately after finishing the last BCI session. Each user had to rate 10 statements on a 5-point Likert scale. Scores are shown in Table 3. The questions are translated from Spanish. All odd positive statements were rated with mean scores higher than 2 (ideal score: 4) while four out of the five even negative statements were rated with mean scores lower than 2 (ideal score: 0). Hence, most participants rated favourably the design, interface, usability and usefulness of the proposed tool. Only the statement 6, about the signal acquisition by means of EEG, was rated unfavourably.

INSERT TABLE 3 AROUND HERE

4 Discussion

In this study, we developed an assistive P300-based BCI tool for controlling electronic devices at home. Fifteen severely disabled subjects interacted with the proposed tool in order to assess its usefulness. Ten out of the fifteen participants were able to adequately operate the application, with accuracies higher than 75%. Eight out of them achieved accuracies above 95%. This is remarkable because they are real end-users of BCI applications, since they present motor impairments. Three out of the remaining participants (P6, P11 and P15) operated the BCI tool with accuracy ranging from 63% to 65%. The remaining two participants (P5 and P13) were not able to suitably manage the assistive application. In the specific case of subject P13, he was not able to perform evaluation sessions with the assistive BCI tool. After three calibration sessions, it was not possible to detect reliable differences in his EEG between the desired option and all other options. This could be due to P13 presented frequent sudden muscle spasms affecting the EEG recordings quality.

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In terms of degree of motor disability, thirteen participants had moderate or severe motor impairments. Two out of them (P5 and P13) were not able to adequately manage the BCI tool. Nevertheless, six out of them (P2, P3, P4, P8, P9 and P14) achieved excellent accuracies, higher than 95%. The remaining users with moderate or severe motor disabilities reached accuracies above 75% (P7 and P10) or moderate accuracies (P6, P11 and P15). Regarding cognitive disability, two participants did not have any cognitive impairment (P1 and P6). P1 achieved excellent accuracy operating the system while P6 achieved 64% accuracy after having repeated Eval1 tasks. In the particular case of subject P6, we observed that he was barely motivated during the experiments. Carrillo de la Peña and Cadaveira [4] showed that the P300 response is affected by non-specific factors, such as the motivation to perform a task correctly. This could be the reason for the poor and unstable performance of user P6 across sessions. The thirteen remaining participants presented mild or moderate cognitive impairments together with motor disability. However, twelve out of them were able to suitably operate the system: seven out of them with accuracies above 95% and five out of them with accuracies ranging from 63% to 84%. In regard to the participants with the worst sustained attention ability (P3, P10, P11 and P15), they were able to adequately manage the proposed BCI tool with accuracies ranging from 63% to 97%. Finally, regarding the most severe subjects (P11, P14 and P15), with both severe motor and moderate cognitive impairments, they achieved results ranging from moderate (63%) to excellent (100%) during at least one of the evaluation sessions. These results are promising taking into account that the population of this study presents both motor and cognitive disabilities. Piccione *et al* [30] showed that subjects with severe disabilities could use a P300-based BCI although their performance was influenced to the degree of impairment. In contrast, the study of Nijboer *et al* [28] proved that the correlation between the online performance with the BCI system and the degree of disability did not achieve statistical significance. Our results agree with the latter study, since statistical significance was not reach between online BCI performance and the degree of motor impairment (r=0.254, P=0.360), cognitive impairment (r=0.116, P=0.680) or attention ability (r=0.134, P=0.634). Nevertheless, in order to analyse the influence on BCIs management of impairment, specific disease and stage of disease additional studies with a larger population are necessary.

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Most of the studies related to BCIs involved healthy people. Nevertheless, severely disabled people are the main end-users of these systems since their personal autonomy can be really increased. Table 4 shows a comparison among seven studies assessing the performance of P300-based BCIs for severely impaired users. The last row summarizes our study. Firstly, Sellers and Donchin [37] found that both healthy subjects and subjects with advanced ALS could use a P300-based BCI using auditory or visual stimuli. Secondly, Nijboer *et al* [28] extended these studies involving severely paralysed people caused by ALS. They were able to use a P300-based BCI that employed a variable-sized matrix of characters for cued and spontaneous text production. Four out of the participants completed the experiment. Their mean accuracy ranged from 46% to 92%. Moreover, Nijboer *et al* [28] performed an exhaustive study over 40 weeks and showed that the amplitude and latency of the P300 potential remained stable over this period of time. Recently, Ortner *et al* [29] analysed the BCI performance of a young healthy population and a group of 15 people with motor impairments. They observed that their impairments affected the performance of the latter group. Thus, the implementation of an automatic removal of artifacts is required. Moreover, adequately adjust the parameters of the paradigm and the environment for each patient is essential. Mak *et al* [24] identified EEG features that correlate with P300-based BCI performance assessed on twenty patients with advanced ALS. Eleven out of the twenty participants were able to achieve accuracy of 100% during at least one copy-spelling run using a 6 x 6 speller matrix. Finally, the study of Spüler *et al* [40] included processing of error-related potentials in order to identify when the classifier did not show the desired result to the user. Error-related potentials information allowed to increase accuracy in both healthy and severely disabled people performance. A population of six severely impaired subjects achieved a mean accuracy of 74% applying this methodology.

INSERT TABLE 4 AROUND HERE

Regarding previous studies related to BCI applications for home automation control, Hoffman *et al* [10] tested a P300-based BCI with five disabled subjects due to different pathologies and four healthy subjects simulating an environment control paradigm. Four out of the five disabled participants achieved 100% offline

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accuracy, as well as two out of the healthy subjects. However, in terms of ITR, healthy subjects reached higher maximum bitrates than disabled subjects. Nevertheless, this study was carried out using a quite different P300 paradigm. One stimuli matrix, consisted of six images that flashed one by one, was used. Moreover, only four sessions comprised of 6 single item selections each were performed. In our study, the BCI application comprises 113 items from 10 menus or matrices, stimuli is presented over rows and columns and two evaluation sessions comprised of at least 42 single item selections were performed. More recently, Aloise *et al* [3] assessed an asynchronous P300-based BCI for virtual environmental control with seven potential end-users. On average, they achieved 72.7% accuracy and 1% error rate in the asynchronous mode. Hence, the system revealed strong reliability in avoiding false positives when the subjects were engaged in other tasks.

Our results show it could be possible to increase the autonomy of severely disabled people by means of assistive P300-based BCI applications. Nevertheless, this study has certain limitations. Firstly, future efforts will be addressed to increase the population under study. It would be desirable that other potential BCI end-users, such as people paralyzed by ALS and/or tetraplegia, took part in future studies. Secondly, the scope of devices that the proposed tool can control is quite large since it encompasses typical devices used in the domestic environment. Hence, further work should be attempted to increase the devices and functionalities that our assistive BCI tool allows to operate. Bluetooth, Wi-Fi or home automation standards could be explored as new control interfaces. Thus, more existent needs at home could be fulfilled. Thirdly, recent algorithmic improvements, such as dynamic stopping of stimulation or asynchronous approaches, could enhance daily use of P300-based BCIs. Stopping methods, both fixed and dynamic, could be highly useful in making P300-based BCIs even more efficient and adaptable to transient changes in data characteristics, both of which are important for long term use of a BCI [36]. Additionally, asynchronous operation allows a more autonomous use of BCI systems by severely disabled people. Aloise *et al* [2, 3] introduced a threshold-based classification approach that allowed eleven healthy volunteers and seven elderly people to divert their attention from the control interface at any time and to increase the accuracy of the

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system during control periods. Therefore, self-paced or asynchronous operation would be more practical for future assistive P300-based BCIs in real life scenarios. Finally, although impaired users might not be able to set up our system without aid of others, our study took a significant step to evaluate the degree to which such populations could eventually operate a stand-alone system.

Most participants rated favourably the design and usefulness of the proposed tool in the questionnaire. However, they rated unfavourably the statement 6, i.e., subjects stated that EEG-based BCIs are not very practical on a daily basis. Some participants suggested the use of dry electrodes and wireless caps in order to make the EEG recording more comfortable and practical at home. Future BCI designs should take into account these suggestions from real BCI end-users.

5 Conclusions

We developed a novel assistive P300-based BCI application for environment control that was assessed by a population of potential BCI end-users in a real scenario. The proposed tool allows to manage 8 real devices, usually present at home, by means of 113 control commands. Fifteen people with different degree of both motor and cognitive impairments caused by different pathologies interacted with the assistive application in their usual environment. Ten out of the fifteen subjects were able to suitably manage the proposed tool with accuracy higher than 75%. Eight out of them achieved accuracy above 95%. Moreover, maximum bitrates up to 20.1 bit/min were reached. Our results suggest the degree of impairment is not a relevant issue in order to suitably operate a P300-based BCI tool. Thus, it could be useful to assist severely disabled people at home, increasing their personal autonomy and independence. In addition, the assistive BCI tool could be easily modified to increase the scope of needs and requirements that can be fulfilled. Hence, their dependence from nurses, caregivers and relatives would be decreased.

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Tables

Participant	Sex	Age	Diagnosis	Motor Impairment Degree	Cognitive Impairment Degree	Sustained Attention Ability
P1	M	61	Arnold-Chiari malformation	A	A	VG
P2	F	44	Acquired brain injury, spastic tetraparesis	S	m	G
P3	F	36	Spastic cerebral palsy	S	m	M
P4	F	52	Extrapyramidal syndrome, dystonia and parkinsonism	M	m	G
P5	F	51	Acquired brain injury, hemiparesis	M	M	G
P6	M	50	Spinal cord injury	S	A	VG
P7	M	57	Neurofibromatosis and severe kyphoscoliosis	S	m	G
P8	M	68	Spastic cerebral palsy	S	m	G
P9	M	65	Spastic cerebral palsy	S	m	G
P10	M	41	Acquired brain injury, cerebral infarction.	M	M	M
P11	F	58	Multiple sclerosis	S	M	P
P12	F	35	Spastic cerebral palsy	m	m	VG
P13	M	47	Spastic cerebral palsy	S	m	G
P14	F	46	Acquired brain injury	S	M	G
P15	F	43	Spastic cerebral palsy	S	M	M

Table 1. Clinical data of all participants in the study.
Sex: male (M), female (F).
Motor/Cognitive impairment degree: absent (A), mild (m), moderate (M), severe (S), profound (P).
Sustained attention ability: very good (VG), good (G), moderate (M), poor (P), very poor (VP).

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Participant	Calibration ACC (in %)	Eval1 ACC (in %)	Eval2 ACC (in %)	Eval2 FT (in %)	Max SR (in item/min)	Max ITR (in bit/min)
P1	100.00	96.55	95.65	100.00	4.17 (7.16)	14.10 (24.20)
P2	100.00	100.00	91.04	100.00	5.89 (14.33)	17.85 (43.42)
P3	100.00	97.06	74.51	100.00	2.64 (3.58)	5.37 (7.30)
P4	100.00	95.00	96.00	100.00	5.89 (14.33)	20.06 (48.80)
P5*	71.43	55.56 / 46.15	-	-	2.23 (2.87)	2.19 (2.82)
P6*	68.86	46.51 / 64.71	-	-	2.23 (2.87)	2.60 (3.35)
P7*	78.57	46.67 / 77.78	-	-	2.23 (2.87)	3.22 (4.14)
P8	91.67	100.00	92.86	100.00	4.17 (7.16)	13.20 (22.65)
P9	96.67	100.00	90.48	100.00	4.17 (7.16)	12.48 (21.43)
P10	82.35	75.76	84.38	70.00	2.64 (3.58)	6.84 (9.29)
P11**	38.89 / 80.00	63.33	-	-	2.23 (2.87)	3.33 (4.29)
P12	87.50	100.00	84.62	100.00	5.89 (14.33)	15.37 (37.39)
P13***	27.78 / 33.33 / 37.50	-	-	-	-	-
P14	95.83	100.00	78.46	100.00	4.17 (7.16)	9.39 (16.12)
P15*	67.86	60.00 / 65.00	-	-	2.23 (2.87)	3.25 (4.18)

Table 2. Results for each participant managing the assistive BCI tool. Online accuracy (ACC) for each kind of session, percentage of finished tasks (FT) during Eval2 session, maximum item selection rate (SR) with the pause between selections (and without the pause between selections in parentheses), and maximum information transfer rate (ITR) with the pause between selections (and without the pause between selections in parentheses).
*: During the third session these participants repeated Eval1 tasks, due to accuracy lower than 70% during the previous Eval1 session.
**: During the second session this participant repeated Calibration tasks, due to accuracy lower than 70% during the previous Calibration session. During the third session, this participant performed Eval1 tasks.
***: During the second and third sessions this participant repeated Calibration tasks , due to accuracy lower than 70% during the previous Calibration sessions.

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	Statement	Score	
		Mean	SD
1	The proposed task (i.e., counting how many times a specific item flickers) is simple	3.20	1.01
2	Flickering stimuli are annoying	1.00	1.13
3	The assistive BCI tool for operating electronic devices at home is useful to increase the autonomy of disabled people at home	3.67	0.49
4	Pictures of each item do not describe suitably the functionality they depict	0.07	0.26
5	The assistive BCI tool would be useful to control other devices at home: blinds, doors, bell…	3.60	0.83
6	Brain activity acquisition by means of EEG with a cap and active electrodes is not very practical on a daily basis	2.53	0.83
7	The assistive BCI tool would be useful out of home for mobility applications	2.53	0.74
8	Navigating through different menus is unnecessarily complex	1.47	0.92
9	The length of each session was suitable	3.33	0.82
10	I would not use this assistive BCI tool again	0.47	0.52

Table 3. Questionnaire results for the assessment of the assistive BCI tool. The questions are translated from Spanish.
Each statement was rated on a 5-point Likert scale (0-strongly disagree, 1-disagree, 2-neutral, 3-agree, 4-strongly agree). Odd statements were positive assertions about the assistive BCI tool (ideal score: 4) while even statements were negative assertions (ideal score: 0).

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Author	Impaired Subjects	Paradigm	Application	Sessions (total item selections)	Sequences	Mean ACC (in %)	ITR (in bit/min)
Sellers and Donchin [37]	3	4 separately words Visual and/or auditive stimuli	4-choice communicator (YES, NO, PASS, END)	10 (120)	25	64.8	0.7
Nijboer *et al* [28]	4*	1 matrix 6x6 or 7x7 Characters Row/column	Speller	20 (660)	4-20	71.9	8.4
Hoffman *et al* [10]	4**	1 matrix 3x2 Images Individual flashes	Environment control at home - Simulated	2 (24)	20-25	100.0***	15.9***
Mak *et al* [24]	20	1 matrix 6x6 Characters Checkerboard	Speller	1 (35)	-	58.0	-
Spüler *et al* [40]	6	1 matrix 6x6 Characters Row/column	Speller with error potentials detection	2 (100)	2-8	74.0	2.1
Aloise *et al* [3]	7	1 matrix 4x4 Images Row/Column	Environment control at home – Virtual Asynchronus operation	2 (75)	1-12	72.7	-
Ortner *et al* [29]	15	1 matrix 10x5 or 6x6 Characters Row/Column	Speller	1 (10)	15	70.7	-
Our study	15	10 matrices 3x4, 4x4 and 5x5 Images Row/column	Environment control at home - Real	3 (134)	3-15	74.4	16.6

Table 4. Comparison of different studies involving P300-based BCIs and severely impaired people. Number of impaired subjects, main details of each paradigm and application studied, number of performed sessions and number of total item selections across all sessions, number of sequences of stimuli, online accuracy (ACC) and information transfer rate (ITR) without pause between selections.

* Four additional subjects were not included since they did not complete the study or algorithms failed to detect reliably the evoked potentials.

** One additional subject was not included since classification accuracies above chance level could not be obtained.

*** Only offline classification results are provided. Four-fold cross-validation was used to estimate the accuracy.

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Figures

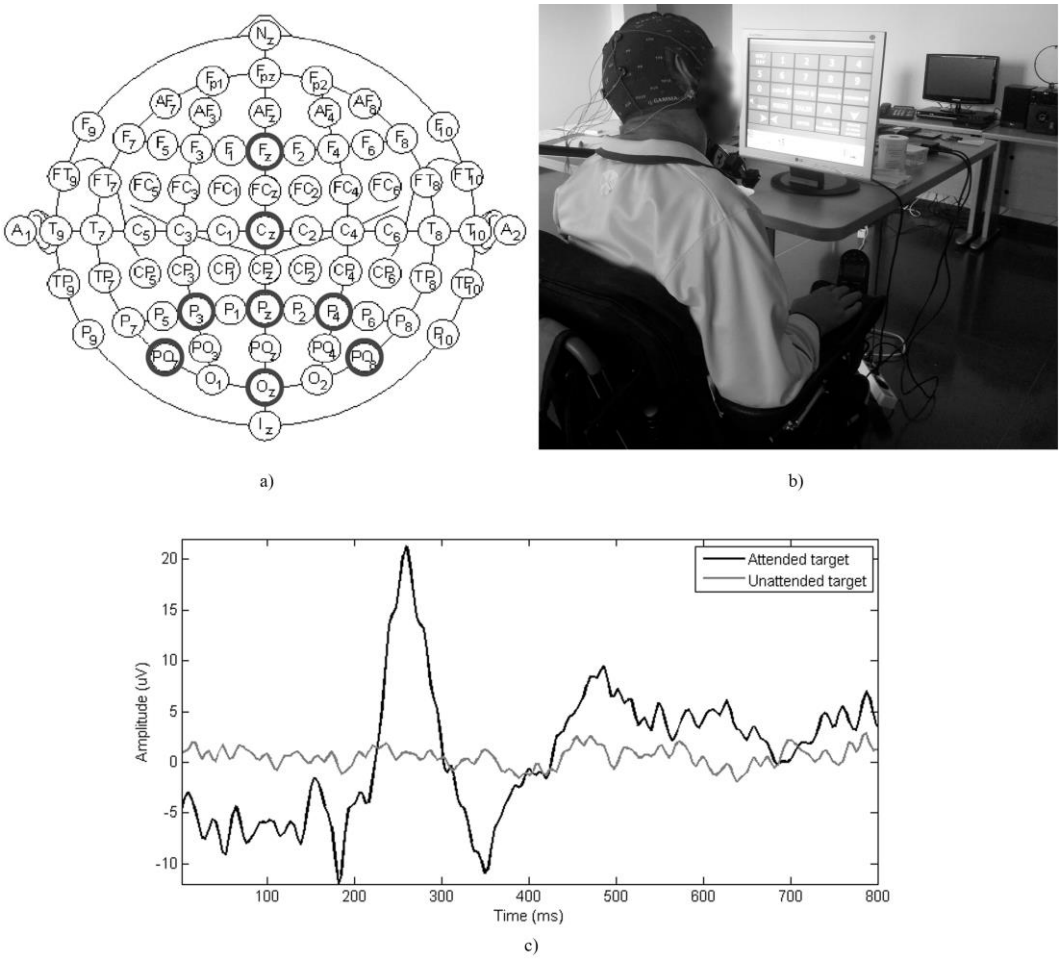

Fig. 1 (a) EEG montage for recording the P300 evoked responses, b) participant wearing the EEG cap connected to the biosignal amplifier during the study and c) P300 waveform: averaged segments containing target and non-target responses at channel Pz.

Fig. 2 Main menu of the developed assistive BCI tool. It shows a 3x4 matrix consisted of images depicting all available devices: TV, DVD player, Hi-Fi system, multimedia drive, lights, heater, fan, and phone. The phone book was included as an independent option in the main menu. Thus, users are able to access from the main menu to a specific submenu of each device and to pause, resume or stop the run.

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a) b)

Fig. 3 a) Submenu for TV managing. It shows a 5 x 5 matrix consisted of images depicting the main TV commands: switch on/off, select a specific TV channel, turn up/down or mute the sound, access and navigate TV menu, access the program guide and return to the main menu. From this submenu, users are able to operate the TV as using a real remote control. b) Specific submenu for phone managing while the second column is dimmed. It shows a 4 x 4 matrix consisted of images depicting the main phone functions: pick up or hang up the phone, dial a phone number (digits from '0' to '9' and '#'), make an emergency call, accessing the phone book or automatic redial the last phone number.

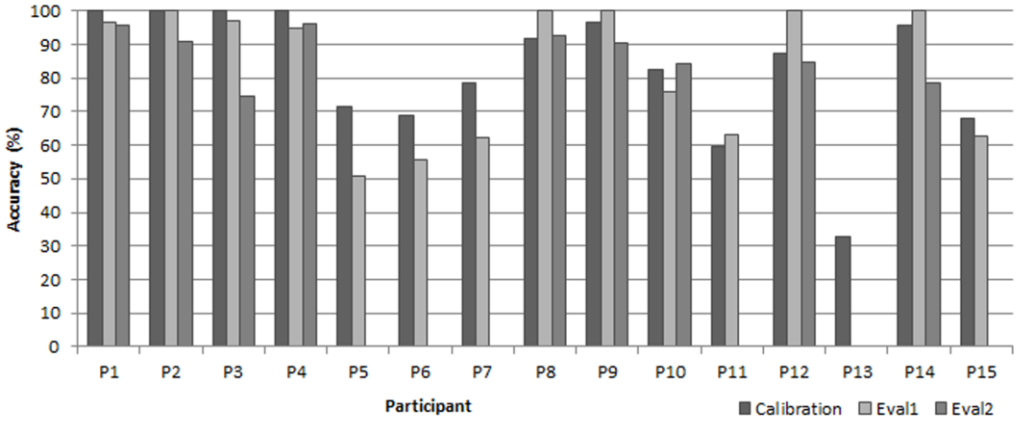

Fig. 4 Results for each participant managing the assistive BCI tool. Online accuracies (ACC) for Calibration, Eval1 and Eval2 sessions are shown.