Development of a simulated living-environment platform: Design of BCI assistive software and modeling of a virtual dwelling place

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HIGHLIGHTS

• SLEP = BCI system + assistive software tailored to motor-disabled people + virtual dwelling place.
• The platform was configured to provide different levels of workload.
• Human–computer interaction is strengthened by user guidance.
• This is important in BCI research, as the prototypes are created for isolated people.
• This approach could avoid the assumption of locked-in BCI users’ requirements.

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ABSTRACT

In brain–computer interfaces (BCIs), the user mental constrains and the cognitive workload involved are frequently overlooked. These factors are aggravated by neuromuscular dysfunction, collateral complications, and side effects of medication in motor-impaired people. We therefore proposed to develop a simulated living-environment platform (SLEP) that was tailored to severely paralyzed people and also allowed the progressive user–system adaptation through increasingly demanding scenarios. This platform consisted of a synchronous motor imagery based BCI system, an everyday assistive computer program, and a virtual dwelling place. The SLEP was tested in 11 healthy users, where the user–system adaptation was evaluated according to the BCI accuracy for classifying the user control tasks. The user heart rate was also incorporated in the evaluation in order to verify the progressiveness of such adaptation. The results of this study showed that user performance tended to increase from the least to the most challenging scenario in learning situations. The results also showed that nine of the eleven users controlled the BCI system in cue-driven mode, completing over half of the tasks. Two of the eleven users controlled the BCI system in target-driven mode, completing two tasks. Taken together, these results suggest that the progressive adaptation in BCI systems can enhance the performance, the persistence and the confidence of the users, even when they are immersed in simulated daily-living situations.

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1. Introduction

Neural progressive disorders, traumatic brain injuries, and strokes may significantly affect the neuromuscular channels, often leading to severe motor disabilities. At their most severe, these neurological disorders can be manifested as locked-in syndrome [1]. The consequences of the resulting neuromuscular deficits are extremely high and more than medical solutions are required to palliate the loss of quality of life and the socio-economic pitfalls. So far, researchers, who work in biomedical engineering, have helped motor-impaired people to regain function by utilizing their remaining movement abilities, their peripheral electrical activity, their brain signals, or combinations thereof [2]. A particular example is the brain–computer interface (BCI), system that decodes users’ brain signals to restore their interaction with the world. A typical non-invasive BCI system records electroencephalographic (EEG) signals that are regulated by users following exogenous or endogenous paradigms. The exogenous paradigm is based on the detection of event-related potentials that are evoked through the attention on auditory, visual or tactile stimuli. The endogenous paradigm depends on the quantification of brain oscillations that are modulated via cognitive tasks such as motor imagery (MI), mental calculation, or association of imaginary words. In line with these two paradigms, it is possible to develop reactive and
active BCIs, respectively [3]. As the present study is limited to MI-based BCIs, we will only refer to active (i.e., via deliberate cognitive task execution) BCIs hereinafter.

To date, the BCI community has been mainly interested in developing assistive technologies (ATs) to enhance the quality of life of locked-in (or otherwise severely paralyzed) patients. These ATs can be encompassed under three broad categories: (1) communication tools that allow the interaction with others, (2) environmental controls that offer the ability to live at home, and (3) mobility systems that provide a certain degree of independence [4–9]. Over the past few years, BCI researchers have focused their efforts on improving user adaptation and system performance. In this respect, they have addressed three main factors: techniques to reduce the number and the length of training sessions, algorithms to select the most suitable EEG features, and methods to increase the classification accuracy among the major number of mental tasks. However, they have rarely investigated human competence (ability to perform a task) and task-oriented demands (workload related to tasks with different levels of difficulty). With regard to human competence, it must be considered that human information processing relies on a limited number of mental resources to transform internal and external stimuli into cognitive responses. Furthermore, the availability of those resources depends on the psycho-physiological state of the person. With respect to the task-oriented demands, the workload involved in BCI systems is frequently overlooked. For instance, the coordination of the BCI control interface could hinder the task at hand, and the repetitive nature of the BCI control tasks might require high levels of attention. This, in turn, may provoke mental fatigue along with aversion and loss of mental focus. Human mental constraints, as well as the cognitive workload issues related to BCI systems, are aggravated by neuromuscular dysfunctions, collateral complications, and side effects of medication in paralyzed people [10–12].

On the basis of the above discussion, we implemented a simulated living-environment platform (SLEP) consisting of a synchronous MI-based BCI system, an everyday assistive computer program, and a virtual dwelling place. The SLEP was carefully designed in accordance with motor-impaired people’s living circumstances, and also, it allowed user learning through increasingly demanding scenarios. After implementing the SLEP, we proceeded to monitor the performance of healthy users at dealing with a variety of tasks under several scenarios. User performance was assessed according to the user ability to master the BCI control tasks, i.e., the highest level at which the BCI system accurately discriminated the control tasks of the user. The effectiveness (in grading the cognitive workload at the SLEP) was also evaluated by recording the user heart rate. This indirect evaluation was based on previous evidence that relates heart rate (HR) deceleration with intake tasks and HR acceleration with rejection tasks [13].

2. Development of a simulated living-environment platform (SLEP)

The SLEP presented here consists of a synchronous (i.e., cue-based) MI-based BCI system, a computer program to assist motor-impaired people in everyday situations, and a virtual dwelling place (Fig. 2.1). The BCI system translated MI (left/right hand movements) and non-MI control tasks into commands for the assistive software. In turn, the assistive software attended to priority demands encompassed under four categories: ‘necessities and desires’, ‘mobility’, ‘environment control’, and ‘messenger’. The navigation through the virtual dwelling place was directed by the ‘mobility’ category of the assistive software. In essence, the functional design of the SLEP was based on seven fields:

- ATs, especially those designed for neuromuscular impairments [15–19],
- augmentative and alternative communication (AAC) tools [20–23],
- BCI communication devices [4,6,7,9],
- smart housing [24–27],
- control of living-environments [8,9], and
- virtual worlds (VW) for neurological rehabilitation [28,29] and BCI applications [30–35].

Furthermore, scenarios with different levels of difficulty were programmed, allowing the observation of the user performance under conditions that gradually increased the following demands: sequential execution of actions, prolonged attention focus, avoidance of interfering stimuli, enrichment of environmental feedback, and coordination of multiple activities.

2.1. Synchronous MI-based BCI system in use

MI is not the only BCI approach for interaction with VEs. Among other viable alternatives we have the so-called SSVEP and P300 approaches, both of which will be incorporated in our system in the future. However, both SSVEP and P300 approaches require absolute focus on the interface, which takes autonomy and freedom away from the user. MI also allows the user to multitask more easily. Hence, the study is focused on MI-based BCI systems.

In active BCIs, users control their brain activity by focusing on a specific mental task such as MI, which has become the most prominent control task used in the BCI community. MI modifies the synchrony of brain oscillators mainly within the α (8–12 Hz) and β (16–24 Hz) frequency bands (although other bands play a role in specific cases as well, e.g., [36]) over the primary sensory-motor cortical area [37]. The deliberate modulation of brain oscillations through MI is not as easy a task as it may seem, especially for users with motor impairments. As users of synchronous MI-based BCIs are often involved in several training sessions prior to the BCI application, these BCIs must have one adaptation phase (offline analysis) and one application phase (online analysis). With these considerations in mind, our BCI system was designed in line with offline and online analyses to distinguish up to three control tasks. The system essentially carried out the same operations on both analyses, taking into account that the online phase requires a device controller. The fundamental structure of the system had six modules: (1) acquisition of EEG signals via Biosemi equipment [38], (2) EEG signal processing concerning spatial and spectral filtering, (3) feature extraction based on band power estimation, (4) feature selection according to Davies–Bouldin Indexes (DBI), (5) feature classification through Fisher Discriminant Analysis (FDA), and (6) plotting of EEG features by using xy-graphs. For further information about the development of the BCI system see [39,40].

2.2. Design of the assistive software and modeling of a virtual dwelling place

A number of published studies related to ATs for neuromuscular impairments [15–19] were consulted to identify the most relevant requirements of motor-impaired patients. The selected requirements were grouped under four categories: (1) ‘Necessities and Desires’, i.e., access to essential services such as body position changes, feeding, toileting, or personal hygiene; (2) ‘Mobility’, i.e., transfer from one place to another; (3) ‘Environmental Control’, i.e., management of electrical devices such as lighting, heating, ventilation, or audiovisual entertainment; and (4) ‘Messenger’, i.e., writing of messages by employing a letter-by-letter formulation strategy (this strategy is the most frequently used approach
Fig. 2.1. Block diagram of the SLEP. The platform is composed of a BCI system (offline analysis, online analysis), assistive software ( ), and a virtual dwelling place. The BCI system essentially converts left/right hand MI signals into binary commands that allow controlling the assistive software. In turn, the assistive software simulates the attendance of everyday requirements, gives auditory feedback emulating the selected activity, and also directs the navigation across the virtual dwelling place.

Fig. 2.2. Assistive software of the SLEP. The top-left interface is the sole presentation of cues. The top-right interface is a generic template of the assistive software layout. The rest of the interfaces are the four tabs of the assistive software titled as follows: ‘Necessities and Desires’ (middle-left), ‘Mobility’ (middle-right), ‘Environment Control’ (bottom-left), and ‘Messenger’ (bottom-right).
The four categories were adapted to a four-tab computer application that was programmed in Python (Fig. 2.2). Every tab was structured using a top-down layout where the panel with the four categories was placed on the top, the menu of each category was located in the middle, and the submenu of each menu was allocated at the bottom. A tiny area below the submenu sections was additionally assigned to record the history of the last selected options. The panel of categories and the menus were designed using a combination of icons and text labels that offered visual interest and fast interpretation. The submenus were created using large buttons, making them an easy target to locate. All text related widgets used high contrast between foreground and background, and the text labels were mainly written by using geometric Sans-Serif typeface to improve the readability on screen. Besides the four tabs, one extra tab was appended to the assistive software (top illustrations in Fig. 2.2). This tab was designed for training purposes and will be described in Section 2.3.

In terms of functionality, the assistive software was predominantly driven by two active commands, taking into account that humans often carry out a binary search among options. Right MIs were translated into horizontal forward movements across the panel of categories and the menus, i.e., navigation commands. Being in the panel of categories, left MIs activated the menu corresponding to the current selected category. Being in the menus, left MIs moved the current selected task of the submenu to the history section. Left MIs were referred as selection commands. The navigation through the submenus was automatically done in order to reduce the mental effort of the user, but it was necessary to maintain a non-MI state while waiting for the self-activation of the task of interest. For navigation-purposes, the current position of the user was highlighted using an orange background, while the forthcoming options were marked by applying large and bold text fonts. Alternations between the menus and the panel of categories were done through specific purpose buttons labeled as “EXIT.” These buttons were included twice whenever possible for facilitating the navigation across the interface. At every alternation, the current available tool bar was colored, whereas the previously used bar was faded. In addition, every time the assistive software rightly recognized either navigation or selection commands, it played a “click” sound indicating success.

The virtual dwelling place (Fig. 2.3) was modeled pursuant to a ground floor unit modified for a quadriplegic person [41], hence also considering many of the locked-in patients’ living circumstances. Note that all the furniture was placed beside the walls to prevent obstructions, and all room doors were removed (with the exception of the bedroom and the bathroom ones due to issues of privacy) to facilitate mobility. This virtual dwelling place was modeled using Blender, free open source 3D computer graphics software [42].

### 2.3. Programming increasingly demanding scenarios

Having developed the SLEP, we configured a variety of increasingly demanding scenarios to provide different levels of workload in the SLEP. We thus tuned both the attention to the environment (intake tasks) and the internal cognitive processing (rejection tasks). The SLEP configuration was organized in four levels: (1) familiarization with the assistive software, (2) user–system adaptation, (3) cue-driven system, and (4) target-driven system. Every level was accomplished by employing two or three specific structured scenarios as described below. The scenarios related to levels 1 and 2 exclusively depended on the assistive software. In contrast, scenarios for levels 3 and 4 used the assistive software along with the virtual dwelling place.

#### 2.3.1. Familiarization with the assistive software (Level 1)

At the first level, there were three scenarios: MI-training (miTR), MI-functionality (miFUNC), and software-training (softTR). In the miTR scenario, users were trained to imagine left and right hand movements (MI control tasks), as well as to be relaxed but focused (non-MI control task). These three control tasks were cued by the unique visualization of an arrow pointing to the left, an arrow pointing to the right, or a square, respectively. All the cues were followed by a warning beep (top-left tab in Fig. 2.2). In the miFUNC scenario, users learned to recognize the functional role of each control task through a generic template of the assistive software. They continued imagining hand movements in accordance with the previous protocol, but left and right cues were additionally reproduced as downward (selection command) and horizontal forward (navigation command) displacements across the generic template (top-right tab in Fig. 2.2). In the softTR scenario, the same mechanism of converting left/right cues into selection/navigation commands was followed, but here it was applied to the assistive software. In the miFUNC and softTR scenarios, the non-MI control task was prompted but it had no effect on the interfaces. Its utility was explained in Section 2.2.

In terms of intake tasks, this level was a learning stage where users interpreted warnings and cues, evaluated the audio feedback, and also decoded the graphics of the generic template and the software interface. In terms of rejection tasks, users imagined left/right hand movements, determined a relaxed and focused mental state, understood the functional roles of the control commands, and also identified the tool set of the software. Note that the sequence of cues, in the two later scenarios, was preprogrammed to promote the interaction with the whole set of tools available on the assistive software.
2.3.2. User–system adaptation (Level 2)

The second level was an interactive stage where users did not only deal with the aforementioned tasks, but were also encouraged to improve their mental performance. At this level, users were involved in an adjustment cycle where the BCI system first adapted to the users (training phase), and later, the BCI system assessed users’ skills to reproduce the control tasks recorded in the training phase. For the training phase, we made use of the softTR scenario by additionally reprogramming the sequence of cues to foster the navigation through the whole assistive software. For the testing phase, instead of converting the cues into their matching commands, the BCI system classified the inward control tasks to decide between a selection and navigation commands. If the BCI system successfully recognized the control tasks, the assistive software executed the corresponding command along with a pleasing tone. If the control task recognition was not satisfactory, an unlucky tone was played and no command was executed on the assistive software. As expected, this scenario was named software-testing (softTS).

2.3.3. Cue-driven system (Level 3)

At the third level, users were immersed into an environment where they needed to maintain attention and had to use the environmental feedback, apart from the BCI concerns. To satisfy these key points, we set an everyday situation where we programmed a sequence of cues that purused the selection of 13 activities of daily living (ADLs) framed by that situation. Therefore, users were not required to plan a navigation strategy because we preset the necessary cues to select the 13 ADLs. When the BCI system failed to predict the cued control task, neither navigation nor selection commands were executed on the assistive software. Following these premises, users never altered the pathway of the pursing ADLs and they were not occupied in redirecting the navigation strategy. We thus avoided the coordination of unexpected activities and the interference of extra stimuli.

As the simulated everyday situation, a sunny morning was selected and users were asked to imagine themselves laying on their beds ready to request daily needs. Those needs were the 13 pursuing ADLs, which were sequentially prompted (middle-left tab in Fig. 2.2) as follows: (1) dressing for a sunny day, (2) going to the bathroom, (3) washing their hands, (4) washing their face, (5) combing their hair, (6) urinating, (7) going to the kitchen, (8) selection of the kitchen submenu, (9) opening the kitchen blinds, (10) opening the kitchen window, (11) eating some fruit, (12) serving cereal, and (13) pouring milk. Every time one of these activities was achieved, the SLEP aurally emulated the activity process or visually simulated the displacement from one room to another. This scenario was named as the level, cue-driven system (cueSYS).

2.3.4. Target-driven system (Level 4)

An equivalent environment to the third level was run at the fourth level, except for the addition of three abilities: the planning of a sequence of actions, the coordination of unexpected activities, and the avoidance of interfering stimuli. Like the cue-driven system, an everyday situation was set along with nine associated ADLs. The necessary cues to select the nine ADLs were not preset in this occasion, so the assistive software always reflected the control command predicted by the BCI system. As the simulated everyday situation, an evening was selected and users were asked to imagine themselves waiting at home for having dinner with their friends.

Based on this scene, the following environmental events were chosen as ADLs: (1) doorbell ringing, (2) woman saying ‘hi’, (3) pouring water, (4) washing their hands, (5) frying bacon, (6) woman saying ‘bye’, (7) passing flatus, (8) brushing their teeth, and (9) yawning. The events were aurally emulated in sequence (bottom-left tab in Fig. 2.2). Every time one of the ADLs was selected, the assistive software audio-visually responded with the corresponding reaction, that is: (1) door opening, (2) not applicable, (3) drinking, (4) going to the bathroom and drying their hands, (5) going to the kitchen and eating, (6) not applicable, (7) going to the bathroom and using the toilet, (8) rinsing out their mouth, and (9) going to the bedroom and making sounds of snoring. The scenario was titled as the level, target-driven system (tgtSYS).

3. Methods

3.1. Participant recruitment

Eleven participants were recruited for this study, which was previously approved by the Ethics Committee of the University of Essex. All of them were informed about the experimental procedure before starting the study. None of them reported auditory impairments and/or neurological disorders, nine of them had normal vision, and two of them had corrected-to-normal vision. Their average age was 37.4 years ranging from 25 to 60 years. There were six right handed males and five right handed females.

3.1.2. Organization of the experiment

The experiment was organized into three sessions. Each session lasted between 120 and 180 min and followed a similar procedure. The procedure included three phases: (1) electrode mounting, (2) determination of the individual alpha frequency (herein abbreviated as IAF and denoted as f_α) according to the peak frequency method, that is described in [43], and (3) fulfillment of three scenarios per session. The aforementioned SLEP levels, along with their respective scenarios, were arranged per session as follows:

- session 1, familiarization with the assistive software (miTR1, miFUNC1, and softTR1);
- session 2, user–system adaptation followed by cue-driven system (softTR2, softTS2, and cueSYS2); and
- session 3, user–system adaptation followed by target-driven system (softTR3, softTS3, and tgtSYS3).

The miTR, miFUNC, softTR and softTS scenarios (as a group will be hereinafter referred as learning-purpose scenarios) had from one up to four runs depending on the user performance. After every run, last-in EEG data were analyzed offline to assess the discriminability among the control tasks. This parameter was estimated on the basis of classification accuracy, as explained in Section 3.3. If users achieved a classification accuracy greater than 70% before completing the four runs of the ongoing scenario, they were moved onto the next scenario. If users failed to reach at 70% of classification accuracy and they had already completed the four runs, the session was continued nevertheless. As there were 80 trials per run (20 lefts, 20 rights, and 40 non-MIs) and each trial was around 8000 ms long, one run took approximately ten minutes and one scenario could last up to 40 min. On the other hand, the cueSYS

1 Activities of daily living (ADLs) is a term in healthcare referring to the daily care activities of impaired and elderly people.

2 The peak frequency method is essentially applied as follows. Firstly, eyes closed (EC) and eyes open (EO) conditions are recorded for three minutes each. Afterwards, the power spectral density (PSD) is obtained for both conditions so as to obtain two spectrums: $PSD_{EC}$ and $PSD_{EO}$. Finally, the IAF is determined by comparing the highest frequencies in $PSD_{EC}$ and $PSD_{EO}$ between 7 and 14 Hz.
and tgtSYS scenarios (as a group will be hereinafter referred to as driving-purpose scenarios) were terminated either when all the tasks (selection of ADLs) were completed or when users decided to give up.

3.1.3. Timing protocol
Each trial lasted between 7000 and 8000 ms and consisted of three phases: warning (0–1500 ms), control task (2500–5000 ms), and blank screen (5000–7000 ± 1000 ms). The warning phase was adjusted to 1500 ms to stimulate an optimum readiness state. The control task was arbitrarily limited to 3500 ms (as this is within the typical task length used in MI-based BCIs), while the relaxation span varied between 2000 and 3000 ms guaranteeing a proper recovery of the brain oscillators. For the MI control tasks, we instructed the participants to imagine themselves opening and closing their hands at their ideal pace. For the non-MI state, we asked the participants to be relaxed but focused.

3.2. Recording of the biosignals ECG, EEG, EMG, and EOG
The biosignals were recorded via Biosemi® equipment, the integration of the ActiveTwo system and the ActiView computer software. The ActiveTwo system was used for acquiring the signals within a 400 Hz bandwidth at 2048 S/s. The ActiView program was configured for decimating the signals to 256 S/s, limiting the effective bandwidth to 52 Hz. EEG signals were recorded by means of 64 active electrodes, together with a driven-right-leg electrode and a common-mode-sense electrode. These electrodes were mounted on a head cap labeled as stated in the 10/10 system [44]. In addition, eight external electrodes (Ext1–Ext8) were included to register the electrical activity from the heart (ECG), muscle contractions (EMG), and eye movements (EOG). The ECG signal was measured by using the lead I of the Einthoven triangle (Ext7–Ext8). For the EMG registry, we did bipolar measurements based on the flexor carpi radialis of both hands. The left arm lead was Ext3–Ext4 and the right arm lead was Ext5–Ext6. Lastly, we placed Ext1 and Ext2 1 cm below the lateral canthus of left and right eyes to measure EOG activity against Fpz [45]. In the present study, only 15 EEG recording sites (FCz, FC1, FC2, FC3, FC4, CZ, C1, C2, C3, C4, CPz, CP1, CP2, CP3, and CP4) and EOG were utilized. The rest of the biosignals (i.e., EOG and EMG) were recorded for future analysis.

3.3. Analysis of the EEG signals
The EEG signals coming into the BCI system were firstly referenced by using the large Laplacian method, and thereafter, they were reconstructed by segmenting every 500 ms and overlapping at 50%. This process produced 11 segments per EEG signal. Subsequently, the absolute power of these segments was extracted on the basis of theta 1 and sensory-motor band rhythms. The frequency bands were: lower theta (θL) from f1 – 6 to f1 – 4 Hz, upper theta (θU) from f1 – 4 to f1 – 2 Hz, lower alpha (αL) from f2 – 6 to f2 – 2 Hz, upper alpha (αU) from f2 – 2 to f2 – 1 Hz, upper beta (βU) from f1 + 2 to f1 + 6 Hz, and upper beta (βU) from f2 + 2 to f2 + 4 Hz. Bearing in mind that there were 15 EEG signals, 6 frequency bands, and 11 segments per signal; vectors of 990 features were acquired. The EEG segments were denoted as δ1, δ2, . . . , δ11.

After every run of the learning-purpose scenarios, the feature vectors (ν) were grouped per control task and the three resulting clusters were used to estimate 990 DBIs. Thereby, the features within each vector were ranked from the most to the least suitable feature with regard to linear separability among three classes. Having ranked all the feature vectors, the most fruitful features were selected in terms of classification performance. For this purpose, a classification process based on FDA took place as follows. First of all, a classifier to discriminate between MI (both left and right together, UMI) and non-MI control tasks (Unon-MI) was assigned, i.e., c1. Every time c1 recognized a MI, a second classifier undertook the discrimination between left (Uleft) and right (Uright), i.e., c2. Based on c1 and c2, the already ranked vectors were classified every 30 features (30:30:990) reaching 33 classifications (C1→33) in total (see Eq. (3.1)). At the end of the classification process, the BCI system searched the pair of classifiers that achieved the highest classification accuracy. In addition to those classifiers, two feature vectors were selected. These corresponded to the features with the DBIs that best discriminated between MI and non-MI, and between left and right. Herein, these are the named highest quality feature vectors (HQFVs).

\[
C_{1→33} = \begin{cases} 
\nu_{\text{UMI}}(30:30:990), & if \ c_1 \text{recognized a MI}, \\
1 | \nu_{\text{Uleft}}(30:30:990), & \text{if not,}\ 
\end{cases}
\]

\[
c_{1→33} = \begin{cases} 
\nu_{\text{Uleft}}(30:30:990), & if \ c_1 \text{recognized a MI}, \\
1 | \nu_{\text{Uright}}(30:30:990), & \text{if not,}\ 
\end{cases}
\]  

The pairs of classifiers, which were created in the softTS scenarios, were used to predict the control commands throughout the driving-purpose scenarios. Note that those control commands were constituted of features, whose indexes were determined in agreement with the HQFVs that weighted the pair of classifiers in use.

3.4. Evaluation of the users
3.4.1. User performance throughout learning-purpose scenarios
User performance was evaluated at every run in the learning-purpose scenarios (refer to Section 3.1.2). At the run of interest, a DBI-FDA process was undertaken to find the most fruitful system-adaptation in terms of classification accuracy. Therefore, the user performance in learning-purpose scenarios was stated as an array of the highest classification accuracies achieved per scenario. It is important to have in mind that users accomplished a different number of runs per scenario, so all the arrays had specific dimensions.

3.4.2. User performance towards the completion of tasks in driving-purpose scenarios
For driving-purpose scenarios, only completed tasks were considered in the evaluation. The overall performance of the users was based on the performance per task (Ptask). Ptask was calculated by Eq. (3.2), where TC was a true command, N was the number of true commands, and M was the number of false commands that preceded the true command of interest. For the cueSYS scenario, N was the programming sequence of cues that was assigned to each task. On the other hand, M was the number of attempts that were necessary before the BCI system recognized a control command in agreement with the preceding cue. Lastly, TC was the successful recognition of the control command.

\[
P_{\text{task}} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{1}{M_{\text{TC}} + 1} \times 100\% \right). 
\]  

In the tgtSYS scenario, users controlled the SLEP at will, pursuing the selection of nine ADLs. We did not manage the appearing cues; and consequently, we could not decide if there existed a true or a false command as in the cueSYS scenario. For this reason, the track of true/false commands consisted of the following criteria:
• We mapped out the most evident trajectory to complete every task (selection of an ADL) by using the layout of the assistive software. For example, considering the tab ‘Mobility’ of the assistive software illustrated in Fig. 2.2, it can be seen that the current position on the software is ‘Carer-room’ option. If the user goal was moving towards the ‘Messenger’ menu, then the evident trajectory would be determined by the following series of control commands: navigation, navigation, navigation, selection, navigation, and navigation. Having mapped out all the necessary trajectories, we assumed that all the users founded their navigation strategy on these trajectories.

• Temporary deviations from the trajectory at hand were considered false commands. These deviations resulted in the creation of subtasks or false commands, depending on the user position over the assistive software (see flowchart of Fig. 3.1). Subtasks were temporary tasks with the aim of returning to the original trajectory.

• The non-MI control task was always considered as a false command because it had no effect on the software; and owing to the nature of the tgtSYS scenario, it was not possible to guarantee when users made real use of it.

• Only the appearance of expected commands in line with the assumed trajectories, either navigation or selection commands, was regarded as true commands.

• Having created L subtasks, we firstly obtained the performance per subtask ($P_{\text{subtask}}$) as stated in Eq. (3.2). Then, we averaged all the $P_{\text{subtask}}$ that were generated before achieving the task of interest.

### 3.4.3. Overall monitoring of the user cognitive engagement via ECG activity

Previous psycho-physiological studies [13] have demonstrated that the humans’ interaction with the environment provokes variations in their HR. HR deceleration is generally associated with intake tasks and orienting responses. This means that HR decreases as the environmental stimulation is intensified. Oppositely, HR acceleration accompanies rejection tasks and defensive reactions. For example, HR increment has been associated with active processing of information necessary in solving problems. Based on these studies, the ECG activity was measured to estimate the HR as indicated in the Eq. (3.3). In this equation, the HR is measured in beats per minute (bpm), $R$ is the R-wave of a QRS-complex, and $QR_{\text{scenario}}$ is the total number of QRS-complexes per scenario. Once the HR per scenario was registered, we obtained an indirect way to monitor the user cognitive engagement throughout every scenario.

$$HR[bpm] = \frac{1}{QR_{\text{scenario}}} \sum_{i=1}^{QR_{\text{scenario}}} \frac{60}{\text{dist}(R_i, R_{i+1})}. \quad (3.3)$$

### 4. Results

Among the participants who were part of the experiments, users 1 and 11 had previously attempted to control BCIs (not necessarily MI-based systems). Users 3, 6, and 9 had previously participated in experiments involving MI tasks. The rest of the users had never gone through either MI tasks or BCI systems. This means that the majority of the users had not previously controlled a BCI system. It is also important to mention that our BCI system was adjusted to each participant by estimating the IAF at the beginning of every experimental session. The mean IAF was 9.87 Hz ± 0.81.

With these preliminary observations, the monitoring of the user adaptation throughout nine configured scenarios (i.e., miTR1, miFUNC1, softTR1, softTR2, softTS2, cueSYS2, softTR3, softTS3, and tgtSYS3) is summarized hereunder. Apart from these results, a behavioral analysis of the HQFVs is also presented. Notice that the HQFVs under consideration only proceeded from learning-purpose scenarios. The DBI-FDA process for finding HQFVs did not take place in driving-purpose scenarios, as explained in Section 3.3.

#### 4.1. Behavior of the HQFVs across the learning-purpose scenarios

The average actual/predicted classifications (in terms of true positive (TP) and false positive (FP) rates) obtained from the DBI-FDA process are presented in Fig. 4.1. It can be seen that FP rates are not biased towards any of the wrong classes in the majority of the scenarios. The one exception is for left-MI in softTS2, where the TP is not much higher than the ‘predicted right’ FP. In general, the confusion data do not show unusual tendencies. The DBI-FDA process selected HQFVs with a large variety of dimensions, which ranged from 30 to 990 features. Every feature of the HQFVs had a specific source in location, frequency, and time. Those sources were the 15 recording sites, the 6 frequency bands, and the 11 time windows, respectively. Having specified the linear separability (i.e., DBI) and
the source of each feature, the distribution of the HQVFs was graphically represented via 2D histograms (see Fig. 4.2). The x-axis and the y-axis were assigned to the frequency bands and the recording sites, respectively. The axes slots were used to accommodate the 11 EEG segments. The number of occurrences of each feature was weighted by DBI-1 and was identified per color.

The DBI histograms of the HQVFs were arranged per scenario because the main objective was to analyze the behavior of EEG patterns regulated under increasingly demanding conditions. Namely, the HQVFs were task-dependent. In session 1, there was a remarkable tendency to the fronto-central area in miTR1 (Fig. 4.2a), in comparison with the subtle tendencies to fronto-central and centro-parietal areas in miFUNC1 (Fig. 4.2b) and softTR1 (Fig. 4.2c). The $\alpha_U$, $\beta_I$, and $\beta_U$ bands were also notably used in miTR1, unlike miFUNC1 and softTR1, where only the $\alpha_U$ band appeared moderately as a recurrent source. In session 2, there were slight tendencies towards fronto-central and centro-parietal areas, as well as $\alpha_U$, $\beta_I$, and $\beta_U$ bands, in both scenarios (Fig. 4.2d–e). Moreover, the $\delta_I$, $\theta_I$, and $\alpha_I$ bands became important for the first time in softTS2. In session 3, the tendencies were significantly specific in both scenarios (Fig. 4.2f–g). Most of the HQVFs were not only gathered on FC3/FC4 and $\alpha_U$ band, but also, the rest of the feature sources played a minor role.

4.2. User adaptation throughout learning-purpose scenarios

All the users terminated the entire set of learning-purpose scenarios. The number of runs that were executed per user is presented in Table 4.1. As can be seen from this table, every user accomplished a different number of runs. Regardless of the disparity, all the runs were included in the graphical representation of the user performance and the user HR. From Fig. 4.3a, it is apparent that the user performance was relatively stable despite the diverse complexity of the scenarios. As a case in point, we can notice that the medians of the box-plots fluctuate from 62% in miTR1 to 70% in softTR3. It is also important to remark that the median in the less challenging scenario (65% on miTR1) negligibly varies, in comparison with the most challenging scenario (67% on softTS2). If we now turn to analyze the user HR, there was a seeming diminution of the HR conforming to the difficulty of the scenario augmented. It is apparent from the box-plots in Fig. 4.3d that the medians constantly diminish from 77 bpm in miTR1 to 69 bpm in softTR3. However, the only significant decrease of the HR was from miTR1/miFUNC1 to guiTS scenarios ($p_{mi\text{TR}1-gui\text{TS}2} = 0.022$, $p_{mi\text{TR}1-gui\text{TS}3} = 0.024$, $p_{mi\text{FUNC}1-gui\text{TS}2} = 0.018$, and $p_{mi\text{FUNC}1-gui\text{TS}3} = 0.014$).4

4.3. User adaptation towards the completion of tasks in driving-purpose scenarios

In the cueSYS2 scenario, nine of the eleven users were able to achieve some or all of the tasks. Specifically, users 4, 5, 6, 7, and 11 completed the thirteen tasks, while users 3, 8, 9, and 10 completed from six to ten tasks. As in the preceding graphical analysis, all the available tasks were considered to monitor the user adaptation in this scenario. Fig. 4.3b provides the user performance in each task ($P_{\text{task}}$ as stated in Eq. (3.2)). Although $P_{\text{task}}$ goes up and down, the median $P_{\text{task}}$ shows a gradual increment from 67% on task 1 to 75% on task 13. Also note that the lowest median $P_{\text{task}}$ is on task 2 (52%) and the highest one is on task 10 (79%). A comparison between these results, and the time consuming task in Table 4.1, reveals that users were capable of managing BCI environments for up to 40 min. Lastly, from Fig. 4.3e we can see that HR medians are very steady, maintaining values under 67 bpm. There was a significant HR diminution between the cueSYS2 and all the learning-purpose scenarios. Specifically, $p_{mi\text{TR}1-cue\text{SYS}2} = 7.54 \times 10^{-6}$, $p_{mi\text{FUNC}1-cue\text{SYS}2} = 1.27 \times 10^{-4}$, $p_{softTR1-cue\text{SYS}2} = 9.3 \times 10^{-4}$, $p_{softTR2-cue\text{SYS}2} = 5.02 \times 10^{-4}$, $p_{softTR3-cue\text{SYS}2} = 0.001$, $p_{softTS2-cue\text{SYS}2} = 0.002$, and $p_{softTS3-cue\text{SYS}2} = 0.005$.

In the tggSYS3 scenario, four of eleven users (users 8, 9, 10, and 11) accomplished two of nine tasks. As shown in Fig. 4.3c, the median $P_{\text{task}}$ of these users is 66% and 74% on tasks 1 and 2, respectively. They spent from 30 to 75 min in this scenario, and they redirected the navigation trajectories from 22 to 66 times. In addition, Fig. 4.3f presents HR medians under 65 bpm. Similarly to the cueSYS2 scenario, there was a significant HR diminution in comparison with all the learning-purpose scenarios. The $p$-values were: $p_{mi\text{TR}1-tgg\text{SYS}3} = 0.006$, $p_{mi\text{FUNC}1-tgg\text{SYS}3} = 0.003$, $p_{softTR1-tgg\text{SYS}3} = 0.037$, $p_{softTR2-tgg\text{SYS}3} = 0.039$, $p_{softTR3-tgg\text{SYS}3} = 0.027$, $p_{softTS2-tgg\text{SYS}3} = 0.039$, and $p_{softTS3-tgg\text{SYS}3} = 0.049$.

5. Discussion

In the present study, we developed a SLEP that was tailored to severely paralyzed people and also allowed a gradual user–system adaptation to the platform. The SLEP was tested on 11 healthy users, where the user–system adaptation was evaluated according to the BCI accuracy for classifying the user control tasks. This evaluation resulted in the estimation of the HQVFs. The user HR was also incorporated in the evaluation in order to verify the gradually interactive properties of the SLEP.

5.1. Behavior of the HQVFs across the learning-purpose scenarios

In general, the classification between left/right MIs and non-MI control task was well-balanced across all the learning-purpose scenarios. The misclassifications (FP rates) were not towards a particular class.

With regard to the EEG recording sites, there was a notable tendency to fronto-central recording sites (particularly, FC2, FC3, and FC4) in miTR1, softTR3, and softTS3. In contrast, there was a more even dispersion between fronto-central and centro-parietal (particularly, CP2, CP3, and CP4) recording sites in the rest of the scenarios. In both cases, the recording sites were around C3 and C4, which are the most frequently used electrodes in MI-based BCI systems [47]. The slight preference for fronto-central areas in some scenarios or for centro-parietal areas in others is difficult to explain, but it might be related to the functional roles of the brain. It is well known that the frontal lobe is associated with attention, short-term memory tasks, and planning; whereas, the parietal lobe is related to the integration of sensory information [48]. The user–system interaction was limited to the visualization of a cue in miTR1, which could explain the minor role of the parietal lobe. In the softTR3 and softTS3 scenarios, users were already familiarized with this type and maybe their attention was only directed to the ongoing control task.

With regard to the frequency bands, the only prevalent band was $\alpha_U$ which is precisely one of the bands wherein the sensory-motor rhythms can be found. The rest of the bands commonly related to sensory-motor rhythms ($\alpha_L$, $\beta_I$, and $\beta_U$) could not appear as expected, because they were largely affected by other events. For example, the $\alpha_I$ band appears widespread over the scalp in general task demands, being fundamentally elicited by the energetic mechanism of arousal, attention, effort, and expectancy [49]. On the other hand, $\beta_I$ and $\beta_U$ bands are also modulated by stimulus assessment and decision making [50]. In the case of $\delta_I$ and $\theta_I$ bands, these were initially regarded as potential...
5.2. User performance throughout learning-purpose scenarios

Although the majority of the users had never been immersed in a BCI environment, the user performance tended to increase from the least (miTR1) to the most (softTS3) complex scenarios. These results are consistent with previous BCI studies and they similarly suggest the two following instances. First, a person can modulate electrical brain activity related to MI, even in highly demanding environments [30,31,35]. Second, the enrichment of the human–computer interaction may diminish the burden of long training sessions, maintaining user attention on the control tasks for a longer period and achieving a better user performance [53]. We furthermore enriched the human–computer interaction by guiding the users, rather than only augmenting the sensorystimulation as is frequently done in applications related to VEs or video games. This drove the users to discover the complex functionality of a completely unknown system by their own experience. In other words, the users taught themselves at their own

Table 4.1

<table>
<thead>
<tr>
<th>Learning-purpose scenarios</th>
<th>Driving-purpose scenarios</th>
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<tbody>
<tr>
<td></td>
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<td>Runs</td>
<td>Runs</td>
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<tr>
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<td>User 11</td>
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a The time scale is in minutes.

candidates for improving classification accuracy (especially in differently demanding scenarios) due to their sensitivity to attention, alertness, cognitive workload, and learning [51,52]. However, the results of this study were rather disappointing because $\theta_L$ and $\theta_U$ bands merely appeared as promising contributors in softTS2. We cannot support the inclusion of theta bands, at least as a discriminator of control tasks.

Fig. 4.1. True positive and false positive rates that resulted in the DBI-FDA classification process. These are average rates across the eleven users.

Fig. 4.2. DBI histograms of the HQFVs per learning-purpose scenario. These scenarios are: (a) miTR1, (b) miFUNC1, (c) softTR1, (d) softTR2, (e) softTS2, (f) softTR3, and softTS3. Every histogram is depicted in accordance with the feature sources.
pace. User guidance has particular importance in BCI research because the prototypes are created for people who are totally isolated from the world. As far as we know, regardless of the application, BCI researchers commonly move from offline to online modes by using remarkably different interactions. This complicates the transfer between modes without a certain level of expertise.

5.3. User performance towards the completion of tasks in driving-purpose scenarios

In the cueSYS2 scenario, nine of the eleven users completed from 6 to 13 tasks in around 30 min. In the tgtSYS3 scenario, four of the eleven users achieved 2 of 9 tasks in around 57 min, redirecting the navigation strategy 46 times on average. Considering the previous experience of the users in controlling BCI systems, these results are significant to some extent. It is likely that the learning-purpose scenarios had been an effective method to provide confidence and autonomy to some of the users. In addition, the exclusive execution of true commands might help to maintain the persistence and the involvement of the users in cueSYS2. On the contrary, users needed to overcome their failures in tgtSYS3, which could explain the significant reduction in the user performance. In both cases, the incompetency of some users to control the SLEP may have been caused by insufficient training, apart from software engineering problems.

5.4. Overall monitoring of the user cognitive engagement via HR

In two particular cases, the user HR decreased conforming to the increase in the scenario difficulty. These were: (1) comparison between the first two (miTR/miFUNC) and the last (softTS) learning-purpose scenarios, and (2) comparison between the learning and the driving purpose scenarios. Although the user HR did not significantly diminish along all the scenarios and it was probably affected by many other factors, these results could be associated with previous psycho-physiological studies [13]. It has been hypothesized that HR deceleration facilitates sensory intake and orienting response because baro-receptor pressure leads to greater cortical activity. As a result, the receptivity of external stimuli is enhanced, producing effective responses and accurate perceptions of the environment. On the other hand, it is also suggested that HR acceleration promotes the rejection of potentially distracting environmental stimuli, allowing attention fixation on internal cognitive processing. Owing to the apparent decreasing trend of the user HR, the first part of the hypothesis (HR deceleration) allows us to suggest that there existed a gradual user–system adaption. Furthermore, the second part of the hypothesis (HR acceleration) might also support these results to some extent. Although there were rejection tasks (such as the control tasks) in the study, all of them depended on the interaction with the environment. Therefore, the users’ reactions were orienting responses, which diminish the HR as well.

The findings, which have been hitherto discussed, are subject to at least four limitations. First, the SLEP was implemented as a cue-based system; therefore, the natural maneuvering of the platform was not possible. At any time, users depended on the cue timing to evoke control commands. Second, the SLEP was exclusively tested on healthy users, reducing the scope of the project in two ways. On the one hand, the users were motivated by external factors (such as the highly interactive properties of the SLEP) but they were not motivated by an authentic desire for being there (intrinsic motivation). The intrinsic motivation can only come from motor-impaired people due to their real necessity of interacting throughout the SLEP. On the other hand, we could not obtain consumer feedback to restructure the design of the SLEP because the healthy users are not the main target population. Third, undesired electrophysiological signals were not eliminated in the course of the experiments, and this might have caused the misunderstanding of some of the control tasks. The elimination of blinks and unintentional motor activity is of particular interest because this electrical activity produces abnormal amplitude peaks in the EEG recordings. This, in turn, frequently results in misclassifications of the EEG patterns. Last but not least, as we attempted to extract information directly from the brain, the SLEP (as any BCI) was very susceptible to the users’ mood. For example, some users showed an excellent performance throughout the learning-purpose scenarios, but they were unable to achieve a task in the driving-purpose scenarios.

Regardless of these limitations, the focus of this study is an important issue for further research. The involvement of the requirements of the “real” target population in the development of BCIs may help to tailor these systems to the capacities and abilities of the consumers. Furthermore, the BCI gradual interaction can become a powerful way of prototyping systems that are designed for people who are totally isolated from the world.
6. Conclusion

This study was undertaken to implement a SLEP with increasingly demanding scenarios, and evaluate if users could succeed in controlling BCI systems under simulated daily-living situations when a progressive user–system adaptation was used. The results of this study showed that the user performance tended to increase from the least to the most challenging scenario in learning situations, regardless of the user inexperience. It was also shown that nine of the eleven users controlled the BCI system in cue-driven mode, completing over half of tasks. Two of eleven users controlled the BCI system in target-driven mode, completing two tasks. Taken together, these results suggest that the interactive guidance in BCI systems enhances the performance, the persistence and the confidence of the users, even when they are immersed in simulated daily-living situations. These results also provide the following insight for future research: the BCI gradual interaction can become a powerful tool of prototyping systems that are designed for people who are totally isolated from the world.

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References


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