

Using a Hybrid Brain Computer Interface and Virtual Reality System to Monitor and Promote Cortical Reorganization through Motor Activity and Motor Imagery Training

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Abstract—Stroke is one of the leading causes of adult disability with high economical and societal costs. In recent years, novel rehabilitation paradigms have been proposed to address the life-long plasticity of the brain to regain motor function. We propose a hybrid brain–computer interface (BCI)—virtual reality (VR) system that combines a personalized motor training in a VR environment, exploiting brain mechanisms for action execution and observation, and a neuro-feedback paradigm using mental imagery as a way to engage secondary or indirect pathways to access undamaged cortico-spinal tracts. Furthermore, we present the development and validation experiments of the proposed system. More specifically, EEG data on nine naïve healthy subjects show that a simultaneous motor activity and motor imagery paradigm is more effective at engaging cortical motor areas and related networks to a larger extent. Additionally, we propose a motor imagery driven BCI-VR version of our system that was evaluated with nine different healthy subjects. Data show that users are capable of controlling a virtual avatar in a motor imagery training task that dynamically adjusts its difficulty to the capabilities of the user. User self-report questionnaires indicate enjoyment and acceptance of the proposed system.

Index Terms—Brain–computer interface (BCI), mirror neurons, motor imagery, neuro-feedback, personalized training, stroke, virtual reality.

I. INTRODUCTION

WITH about 16 million new cases per year [1], [2], the increasing economical and psychosocial impact of stroke demand new diagnostics for preventive actions, more effective

treatments to minimize its sequels, and novel strategies for effective, low cost, and personalized rehabilitation.

In the last decades, important neuroscientific findings have contributed to the understanding of specific brain mechanisms that relate to functional recovery. Nowadays, it is widely accepted that recovery after a stroke relies on neuronal mechanisms that allow nonaffected brain areas to take over functions of the damaged tissue [3], [4]. This is achieved by means of neuronal plasticity, and the recovery possibilities strongly depend on the size, severity, and location of the lesion [5], [6]. Consequently, rehabilitation approaches aim to provide an effective way of driving cortical plasticity and to recruit secondary motor areas to achieve functional brain reorganization [7]–[10].

Recently, the discovery of cognitive processes that mediate between perception and action, such as the mirror neuron system [11], enabled the emergence of novel rehabilitation techniques which specifically target lesions of the central nervous system, such as traumatic brain injuries or strokes [10], [12], [13]. The use of novel information and communication technologies has played a crucial role because they enable neuro-rehabilitation systems to be tailored in such a way to directly tackle the brain mechanisms for recovery. Some examples for motor rehabilitation include virtual reality (VR) [7], [14]–[16], robotic-aiding systems [17], [18], or brain–computer interfaces (BCIs) [19]–[21]. Using VR one can create controlled environments that define training tasks specifically designed to target the individual needs of patients. Furthermore, intensive movement VR training can be embedded in motivating tasks, making use of augmented feedback and reward (see [22] for review). In addition to making personalized training possible, VR also lets patients play a more active role in their rehabilitation process by being able to self-monitor their own improvements.

Most of the existing VR systems are only adequate for a limited amount of patients sharing some specific deficits, and generally require a minimum motor control. This makes it particularly difficult to evaluate the benefits of these novel technologies in patients that are nearly or completely immobilized. One solution is through BCI technology, which has already been used to enable immobilized patients to act and interact with the world solving to some extent the accessibility problem [23]. However, fewer investigations have addressed the use of this technology to facilitate the access of patients to rehabilitation practices and to facilitate neural reorganization [24], [25]. Additionally, more quantitative and comparative data on the effective-

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ness of neuro-feedback interventions in functional terms and their subsequent brain reorganization is needed. This knowledge is essential for designing the most appropriate intervention depending on the specifics of each lesion and prognostic [26], [27]. Therefore, it is crucial to be able to simultaneously monitor functional recovery and plastic changes in the brain during the treatment's progress.

To address the aforementioned accessibility limitations, and to provide monitoring and neuro-feedback capabilities, we have developed a novel hybrid BCI-VR neuro-rehabilitation system. Using synchronized neural activity as an effective way to drive plasticity in the Hebbian sense [28], we propose that the more motor-related systems we are able to engage in our neuro-rehabilitation task, the more likely that secondary or indirect pathways can be recruited and exploited to access undamaged cortico-spinal nerve fibers for motor control [7], [27], [29]. The BCI component of the system has a twofold purpose. First, it is used to investigate the activity patterns of motor-related brain areas to better understand the effects of different motor and imagery training paradigms. Secondly, it is used to implement a neuro-feedback motor training paradigm. Our system aims at giving patients with traumatic brain injury and stroke patients access to novel motor-training paradigms designed to further potentiate functional cortical reorganization by means of neuro-feedback paradigms. This is especially relevant when movement control is severely impaired and active movement training capability (i.e., movement initiated and controlled by the patient) is not present. In this paper, we present a proof of concept study with healthy subjects.

II. PROCEDURES

Our setup consists of a desktop computer that runs the VR environment. Arm movements are performed on a tabletop of about $1.4 \text{ m} \times 1 \text{ m}$. A laptop computer processes the real-time EEG data from the user's BCI, sending control signals to the desktop computer that runs the VR environment.

A. VR Environment

The VR setup is based on the rehabilitation gaming system (RGS), a first-person perspective VR system that combines concepts of goal-oriented action execution and observation with task-oriented learning and model based individualization of training to specifically address the recovery of upper extremity functionality after stroke [15]. The main underlying hypothesis is that through the recruitment of the mirror neuron system, combined action observation and execution can activate the motor system more effectively or extensively [30], thus enhancing or speeding up cortical reorganization by means of plastic changes after a lesion in the brain. The effectiveness of the RGS approach has been shown in two longitudinal clinical interventions [31], [32]. One of the main limitations of the RGS in its current form is that it is only accessible to patients who already have a sufficient level of motor control to perform the physical training. Unfortunately, this means that patients with lower motor control, those who require more extensive rehabilitation, cannot benefit from this novel neuroscientific and technology-driven approach. Consequently, the presented system in this paper consists of an extension of the RGS system

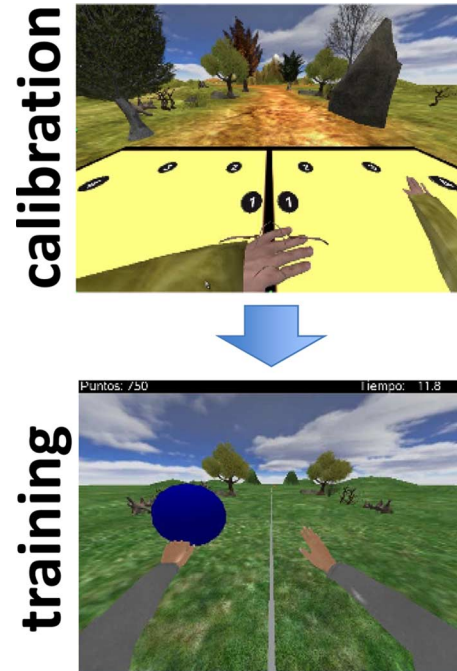


Fig. 1. RGS training consists of two phases: calibration and training. The calibration phase is used to compute the speed, latency, and range of the movements of the avatar when reaching for specific locations marked on a virtual tabletop (top panel). The parameters computed in the calibration phase are used to set the starting difficulty of the training phase. During training, the user is asked to control the arms of the avatar and intercept incoming spheres. See [15] for a detailed description of the RGS training task.

that integrates a BCI to assess brain activity patterns via EEG recordings, and implements a training paradigm using mental imagery for patients who lack active movement of the upper extremities.

The implemented training is a game-like task in which the user has to intercept incoming spheres by moving the arms of a virtual avatar. The parameters that define the difficulty of the task (speed of spheres, sphere distance from arm resting position, and time interval between spheres) are computed at the start of the game in a calibration task (Fig. 1 top panel). Parameters computed from this calibration are used to set the starting parameters of the training task. Training parameters are then adjusted during the game by an intelligent controller that sets the difficulty to be neither too easy nor too difficult, to sustain motivation and individualize the training to the patient's capabilities. In addition, the system provides extra feedback to the user to monitor his/her progress in the form of a score during the game and performance summaries at the end of the training session.

B. Brain-Computer Interface

It is well established that motor intent or imagery generates an activation of cortical motor areas similar to those engaged during the execution of motor actions [33]. The neural activity during these tasks generates electric waves that can be measured from sensors located at the surface of the scalp (i.e., EEG). Our BCI component is setup to measure EEG activity from primary and secondary motor areas.

Data Acquisition and Analysis: The EEG raw data were acquired by means of a g.USBamp biosignal amplifier (gtec, Graz,

Austria) connected to Au-gold surface electrodes with a 1.5 mm medical safety connector. The g.USBamp amplifier has 16 ADC channels with a 24 bit resolution (<30 nV) and an update frequency of 256 Hz. The biosignal amplifier was connected via USB to a laptop running Simulink 2007a (MathWorks Inc., Natick, MA, USA). Gtec's g.HISys (simulink high-speed on-line processing library) was used for recording and online processing the EEG data. Matlab 2007a (MathWorks Inc., Natick, MA, USA) was used for the offline data analysis. We used caps with predefined electrode placement locations based on the standardized international 10/20 system to allow for precise and reproducible electrode placement when measuring [34]. Given that the placement of the electrodes in our setup did not measure from the most frontal areas, eye movement filtering was considered unnecessary.

C. Experimental Design

Although some data about motor activity and imagery tasks exist [13], [35], [36], it is not yet clear what, if any, specific benefits a combined approach could bring. To address this question we designed two experiments. The first is a mapping experiment used to assess how brain activity—more specifically at the sensory-motor areas—is modulated by different training paradigms. The second is a BCI experiment designed to evaluate the feasibility of the system to be exclusively controlled using motor imagery.

Mapping Experiment: Nine naïve right-handed healthy participants ($M = 26.4$ years old, $SD = 4.2$) participated in the mapping experiment. The BCI configuration consisted of nine electrodes covering somato-sensory and motor areas (positions F_3 , C_3 , P_3 , T_3 , F_4 , C_4 , P_4 , T_4 , and C_z ; while A_2 was used as reference). Raw data were filtered into α/μ (8–13 Hz), β (12–30 Hz), and γ (30–100 Hz) frequency bands.

Data of actual arm movements tracked with a camera while performing the training game was used to create a set of pre-recorded movement sequences (each 5 min long) to be reproduced by the avatar. Each sequence had a balanced number of left and right arm movements, which were presented randomly during the experiment. For each of the experimental conditions one sequence was randomly selected. Furthermore, the presentation order of the following conditions was randomized.

- **Passive observation** of the movements of the avatar. The subject was asked to not perform any motor action and only observe the arm movement sequence. This condition was used as control condition for the following motor and imagery conditions.
- **Motor activity** simultaneous with observation. The subject was asked to imitate the movements of the avatar, resulting in simultaneous action and observation of movements.
- **Simultaneous motor activity and motor imagery.** The subject was asked to imitate and mentally imagine the movements of the avatar, resulting in simultaneous motor imagery and motor action.
- **Motor imagery** simultaneous with observation. The subject was asked to imagine himself/herself imitating the movements of the avatar, resulting in simultaneous motor imagery and movement observation.

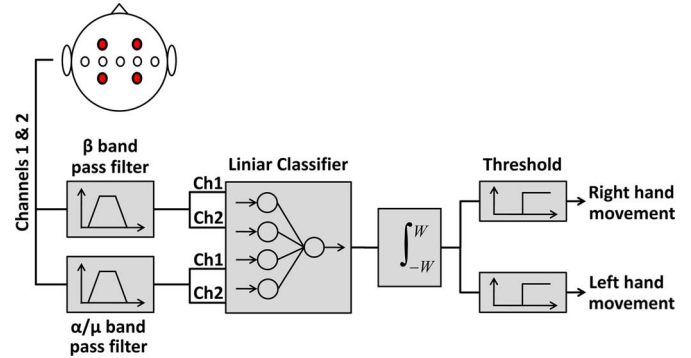


Fig. 2. Online sensory motor rhythm detection model used in the complete BCI—motor imagery experiment. Two bipolar derivations are used in positions $FC_3 - FC_4$ and $CP_3 - CP_4$. The online model implements a linear classifier that detects right versus left arm motor imagery. Arm movement decisions are taken after computing the moving average of the output of a linear classifier, and minimum confidence thresholds are reached.

BCI Experiment: Nine different naïve right-handed healthy participants ($M = 28.3$ years old, $SD = 5.3$) participated in the BCI experiment. For this experiment, we used two bipolar derivations electrodes over the somato-sensory and motor areas (FC_3-FC_4 and CP_3-CP_4). FP_z was used as ground and A_2 was used as reference. In this configuration, only α and lower β frequency bands of the EEG data were considered. A classifier based on the analysis of sensory motor rhythms (SMR) was used to detect right arm movement imagery, left arm movement imagery or no motor imagery. SMR is an oscillatory rhythm of synchronized neural brain activity in the α and lower β frequency bands that is measured in sensory-motor areas in the absence of physical or imagined motor activity [37] (Fig. 2).

A two dimensional linear classifier to detect the lateralization of the SMR was trained by each user imagining 40 times either a right or left arm movement for 8 s in a computer-mediated protocol prior to using the training system. A moving average was applied to the classifier output to compute the data baseline and to correct the data for slow drifts. The classifier reported three values: no movement detected, right arm movement, or left arm movement. The amount of time that an arm movement was detected defined the amount of arm extension. The computed position of both virtual arms was sent to the VR environment at every time step by means of a UDP network connection. The movement range of the virtual arm allows reaching an object in any position of the peripersonal space. We define a nonextended arm as having the end effector in front of the torso, and fully-extended as full lateral extension. The experiment consisted of four phases: training of the BCI classifier (380 s); calibration phase of the training game (7 min); training game (10 min); and a self-report questionnaire. Both the calibration and the training phase were performed exclusively using motor imagery.

D. Self-Report Questionnaire

A five-point Likert scale questionnaire (1 = lowest, 5 = highest) containing 23 multiple-choice questions was designed to collect subjective data after the second experiment. The questionnaire was divided into five different blocks, although these blocks were not made explicit to the user, and the order of questions was randomized. **Enjoyment:** Assessed the level

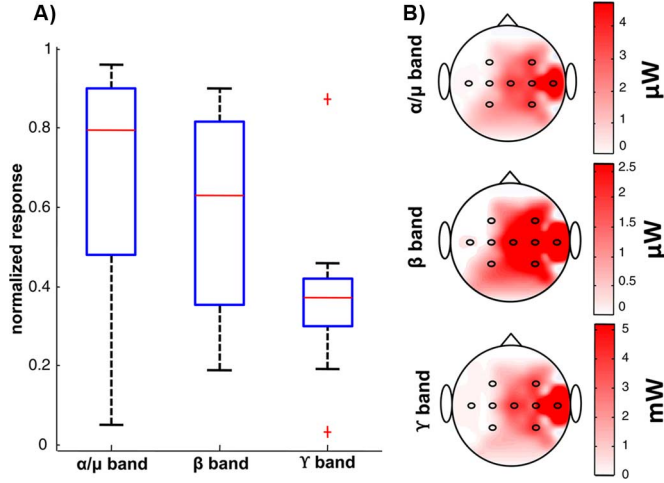


Fig. 3. Analysis of the average brain activity for α/μ , β , and γ frequency bands in the passive observation experimental condition. A) Normalized mean response values. B) Mean brain activity maps (power). Data correspond to the average activity during the duration of the experimental condition.

of fun and enjoyment that subjects felt and their predisposition to repeat the experiment. *Learning*: Evaluated the degree of perceived learning of the participants during the experiment. *Ease*: Assessed the level of difficulty of the proposed tasks. *Control*: Evaluated the level of perceived control over both virtual arms. *Configuration*: Assessed as the appropriateness of all settings of the system, including those that adjust the difficulty of the game (speed and range of balls, time interval between balls, and speed of system response).

III. RESULTS

The BCI-VR system presented here investigates the combination of personalized motor training exploiting brain mechanisms for action execution, observation, and mental imagery as a way to engage secondary or indirect pathways to access undamaged cortico-spinal tracts. Mean activity brain maps (power) and statistics for each frequency band (α/μ , β , and γ) were computed for the passive observation (control) condition (Fig. 3). This analysis shows that most of the activity during passive observation is concentrated in lower frequency bands, decreasing as frequency increases. The higher levels of activity in the α/μ and β bands are consistent with persistent synchronized activity levels in the motor areas when no motor activity is involved [33].

A comparative analysis of the remaining conditions allows determining the specific contributions of each experimental condition. Mean activity brain maps of synchronized neural activity and their related statistics are computed for each frequency band and experimental condition compared to the control condition. Since the data were not normally distributed the nonparametric Friedman's test was used to assess the effect of each experimental condition on mean activity in the sensory-motor areas. Individual power response values were normalized for each subject for the comparative analysis (Fig. 4). Condition effects were found significant for all frequency bands (α/μ band $\chi^2(2) = 4.333$, $p = 0.0131$; β band $\chi^2(2) = 6.22$, $p = 0.0446$; and γ band $\chi^2(2) = 6.89$, $p = 0.0319$).

- α/μ band: Interestingly, the simultaneous motor activity and imagery condition triggers enhanced neural synchronization ($Mdn = 0.81$) as compared to either the motor activity ($Mdn = 0.22$, $Z = 2$, $p < 0.05$) or the motor imagery ($Mdn = 0.52$, $Z = 2$, $p < 0.05$) conditions (matched pairs sign test) [Fig. 4(a)].
- β band: Generally related to alertness, attention or active thinking [38], and in particular hosting the SMR, we observe that the motor activity condition and the imagery condition trigger similar activation patterns [Fig. 4(b)]. We find that the motor activity condition shows de-synchronization ($Mdn = 0.18$) whereas the motor activity and imagery condition shows enhanced synchronization ($Mdn = 0.81$), which is significantly different (matched pairs sign test, $Z = 2$, $p < 0.05$) [Fig. 4(a)].
- γ band: The motor activity condition shows the lowest synchronized activity level, below the level of the passive observation condition [Fig. 4(b)]. Interestingly, both imagery conditions present a bimodal activity map, meaning synchronous activity enhanced in the central areas and inhibited towards the right temporal lobe. Significant differences were found between the motor activity ($Mdn = 0.18$) and motor imagery ($Mdn = 0.87$) conditions (matched pairs sign test, $Z = 2$, $p < 0.05$) [Fig. 4(a)].

A. BCI Experiment

In the second experiment, nine healthy participants used the complete BCI-VR system loop. That is, controlling the movements of the virtual arms only by means of motor imagery. The goal of this experiment was to validate the functioning of the system at the technical and usability levels. The calibration phase was used to compute the baseline parameters for the training task and to assess the level of control of users when asked to move the virtual arms to specific positions (precision control). Chance level in this task is 1/3 given that there are three possible BCI classifier outputs: right arm extension, left arm extension, and no extension. Data shows that participants were able to control the virtual arms above chance level (Wilcoxon signed-rank test, $Mdn = 54.12\%$, $Z = 2.8$, $p = 0.005$). During the game, participants were not requested to perform a precision control of the virtual arms—as in the calibration phase—but to perform a functional control to intercept incoming spheres (Fig. 5(a), top panel). Functional performance was assessed as the percentage of correct sphere intercepts. Data show that users had better functional control than precision control, a median of 85% correct intercepts [Fig. 5(b)]. As consequence of high functional control over the virtual arms, we observe that the adaptive difficulty training module of the RGS starts increasing the difficulty of training, reducing the time interval between spheres, and increasing their speed and dispersion in the peripersonal space of the virtual avatar (Fig. 5(a), bottom panels). A comparison between right and left arm control performance during the training task revealed that subjects could control better their left arm than their right arm (t-test, $p < 0.05$). Interestingly, this was not the case during the calibration task. In fact, a correlation analysis between the virtual

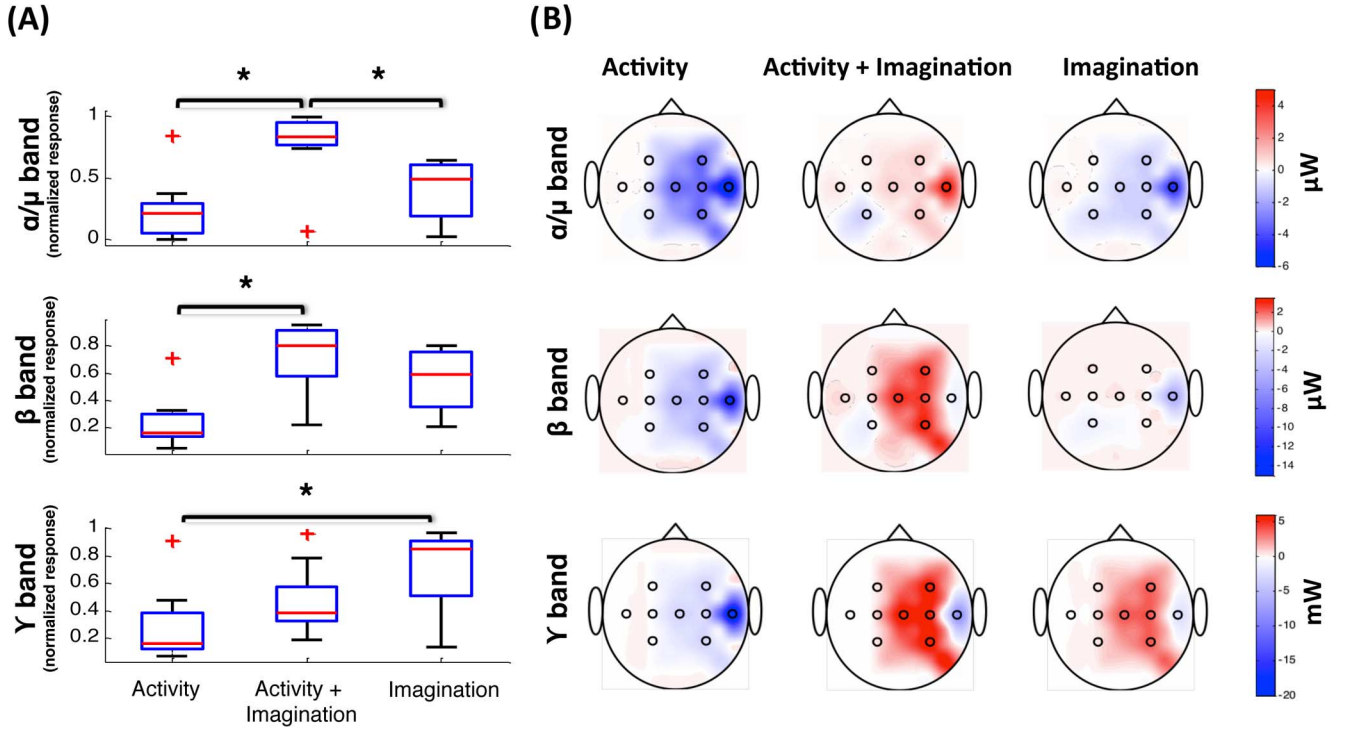


Fig. 4. Analysis of brain activity for the different experimental conditions. A) Normalized mean response values for α/μ , β , and γ frequency bands in each experimental condition. Line (red) indicates the median and the whiskers the 5 and 95 percentiles. * indicates $p < 0.05$, matched pairs sign test. B) Differential mean brain activity maps (power) after correction with the control condition. Blue indicates de-synchronization of neural responses and red enhanced synchronization of neural responses as compared to the control condition.

calibration and the training performance showed no significant correlation.

At the end of the training session, participants were asked to answer a questionnaire (Fig. 6). Overall, participants enjoyed the training session ($M = 4.07$, $SD = 0.47$). In terms of their sensation of fun and predisposition to play again, felt they learned how to control the virtual avatar during training ($M = 4.15$, $SD = 0.49$), thus experiencing a clear learning process along the 10 min of training. However, they did not find the task easy ($M = 2.5$, $SD = 0.92$), meaning that it was difficult to control the avatar's arms ($M = 2.52$, $SD = 0.66$). When asked about the configuration of the system, participants rated the system configuration as appropriate ($M = 3.75$, $SD = 0.55$).

IV. DISCUSSION AND CONCLUSION

The data we obtained during the mapping experiment is consistent with previous studies [33], [39]. More specifically, our findings corroborate that activity in the α frequency band is generally associated with aspects such as relaxation, closed eye-lids and, the most important for our study's purpose, de-synchronization is associated with inhibition control or motor responses (see [40] for review). While suppression of activity in the μ band has been recently associated with activation of mirror neurons [41], all our four experimental conditions are designed to activate the mirror neuron system to some extent because they include either the generation of an action, its imagination, and simultaneous observation. Therefore, the inhibition in this band cannot be attributed to the activation of the mirror neuron

system. Instead, the role of the α band in inhibition control, i.e., timing of inhibitory activity in different locations across the brain, might be the most probable explanation to the supra-additive interaction found in the simultaneous motor activity and imagery condition, where presumably more systems are engaged in the task ($p < 0.05$) [42]. According to the literature, data on the β band contains the SMRs and correlates with active concentration, busyness, and alertness [40]. If this assumption is correct, the brain map measured in the motor imagery condition would indicate a similar level of concentration or alertness as for passive observation. Data on the motor activity condition indicates a reduction of the level of alertness and concentration, being significantly lower than that of the simultaneous motor activity and imagery condition ($p < 0.05$). Thus, the latter condition seems to engage the user more strongly in the training task, maintaining or stimulating concentration to a larger extent. Nevertheless, we cannot attribute the differences found in the simultaneous motor activity and imagery task to an attentional factor considering the experimental data obtained. The fact that this condition also shows activity levels in the α band well above the other conditions cannot be attributed to attentional factors, which are generally associated with the β band. Thus, our data supports the idea that this particular experimental condition engages not only attention but also additional systems.

There is a large body of literature that supports the hypothesis that γ oscillations are related to cross-modal processing and binding [43]–[46] or associative learning [47]–[50]. Data on both imagery conditions are consistent with the idea of an enhancement of cross-modal processing, most remarkably the

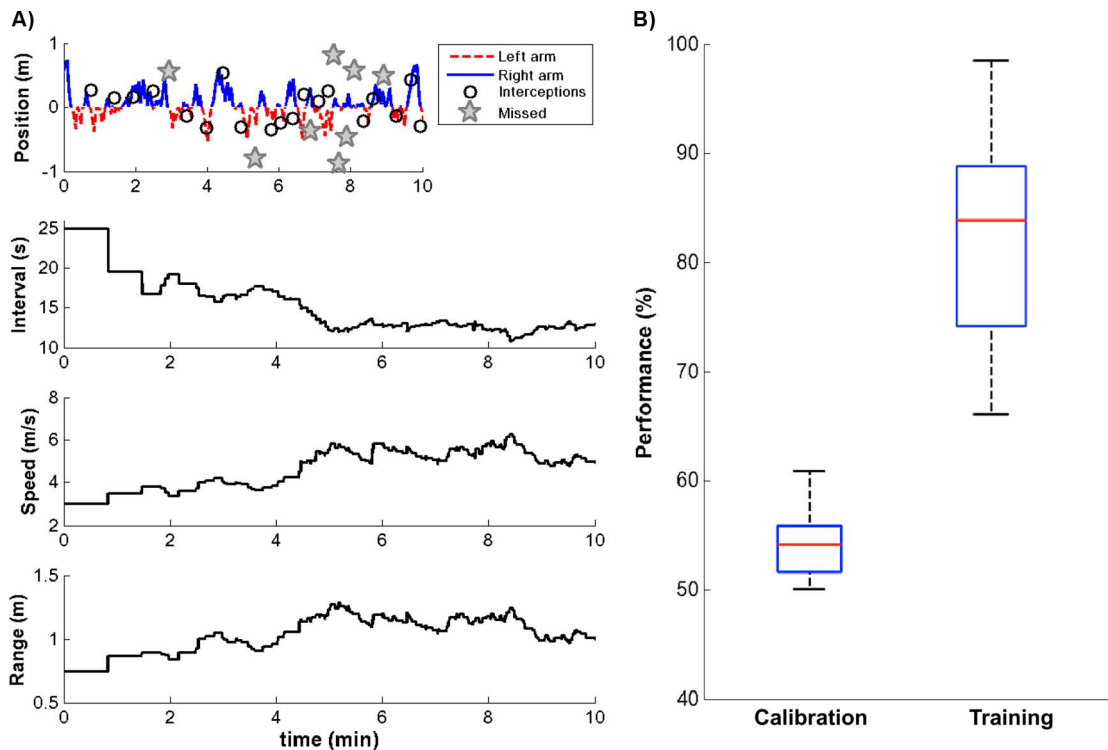


Fig. 5. Analysis of the BCI controlled training task. A) The topmost panel shows the arm extension values (left arm dashed, right arm solid) and the position of game events (missed and intercepted spheres) for participant 1 during the 10 min of training. The three bottom panels show the evolution over time of the training parameters. Data indicate an increase of task difficulty over time (lower interval and increased speed and range). B) Performance of users in the calibration phase—measured as % of time that the user can drive the correct arm—and training phase—computed as % of successful interceptions. Line (red) indicates the median and whiskers the 5 and 95 percentiles.



Fig. 6. User experience evaluation. Users rated on a five point Likert scale 23 questions about enjoyment, learning, ease, control, and configuration aspects of the complete BCI driven system. Bars indicate mean values and whiskers standard deviation. See text for further information.

motor imagery condition ($p < 0.05$). Given the absence of tactile, sound or force feedback during the interaction with the spheres, our data could indicate that both imagery conditions are able to simulate some of those missing modalities. This would be consistent with γ band enhancement for audio-visual and haptic cross-modal binding [43], [45], [51]. However, in order to support this hypothesis, additional experiments using haptic feedback and sound are required. The larger modulation of the activity of the right brain hemisphere for all frequency bands and conditions is consistent with results that support the existence of a transcallosal inhibition from the left to the right hemisphere capable of overwhelming the activity of the right hemisphere [52]. In this experiment, aspects such as the effect of the

experimental condition on the level of engagement in the task [53] or the modulation of the sense of presence [54] or ownership [55] can be crucial for explaining the different brain activity patterns. Unfortunately, the self-report questionnaire used in this experiment did not address these aspects.

The BCI neuro-feedback experiment showed that two bipolar derivations are sufficient to detect SMR and to perform training in our VR environment, achieving a successful functional performance of 85%. However, precision control of the arms is much lower. Additionally, we have shown that the BCI-driven system is able to adapt to the user's capabilities in real-time, thus providing a personalized and motivating training trajectory. User self-reports show high acceptance of the complete BCI-VR system. Enjoyment and learning are the best-rated aspects (4.07 and 4.15, respectively). Because all users were naïve, learning could account for the lack of correlation between the performance during calibration and the training task. In fact, subjects reported that they improved their control of the virtual arms as the task progressed, and that they would perform better if they could repeat the task. Overall, the weakest aspect of the system as rated by the participants is the difficulty of controlling the actions of the avatar. This could be mostly due to the lack of previous training and experience in this task, but also to the fact that the BCI in its current form only exploits two bipolar derivations to control the avatar.

Our paper has presented the rationale and development of a hybrid BCI-VR neuro-rehabilitation system that builds on an effective rehabilitation tool, the RGS [31], [32]. The presented

system extends the RGS to be accessible to patients with a very low degree of motor control. This concept would allow the system to be used starting just a few days after stroke, when the brain is undergoing many plastic changes. Our experimental data confirms that a dual motor activity and imagery training paradigm is able to recruit more task-related networks than the rest of conditions, making this a potentially important factor to enhance functional brain reorganization to improve motor control. These results are promising and important for the development of future neuro-feedback rehabilitation systems since they suggest a new training paradigm that could be more effective at mobilizing cortical plasticity and functional recovery after a brain lesion than current rehabilitation systems. Further, this approach makes VR training available to patients with worse prognostic who do not have access to these technologies. Additionally, we have validated the feasibility of the system using a imagery based paradigm. Through the inclusion of additional electrodes and more sophisticated data classification systems the performance of our BCI could be improved and a better control provided to users. Nevertheless, the suitability of this system for stroke or traumatic brain injury patients still remains to be proven.

In future experiments, the system will incorporate a dual motor and neuro-feedback paradigm. Research on severely affected patients has shown that recovery is usually accomplished by recruiting contralateral networks, whereas for patients showing a higher recovery level it is by means of ipsilateral networks [56]. Hence, a future system should also be able to diagnose patients and provide an appropriate neuro-feedback paradigm priming either ipsilateral or contralateral reorganization depending on the patient's prognostic.

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