Optimizing Motor Imagery Neurofeedback through the Use of Multimodal Immersive Virtual Reality and Motor Priming

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***Abstract*— Stroke is among the leading causes of long-term disability, leaving an increasing number of people with cognitive and motor impairments, loss of independence in their daily life and with a high societal cost. So far, the development of Brain–Computer Interfaces (BCIs) that translate brain activity into control signals in computers or external devices provide new strategies to overcome stroke-related motor limitations. Recent studies demonstrated the brain's capacity for functional and structural plasticity and recovery even in severe chronic stroke. However, it is not fully clear how we can exploit the neurobiological mechanisms underlying recovery. This is the case for restorative BCI research. There is currently no standardized and accepted treatment for the use of BCIs with patients suffering from acute or chronic motor impairments. In this study we investigated with 9 healthy participants the role of multimodal virtual reality (VR) simulations and motor priming (MP) in a motor imagery BCI training. Our findings show improved BCI performance for VR and MP conditions, as well as the capacity to modulate and enhance brain activity patterns. Our data suggest that both VR and MP can be useful to promote neural activation and neuroplastic changes in the rehabilitation of stroke patients in a motor imagery neurofeedback paradigm.**

Keywords*— Stroke rehabilitation; Brain-Computer Interfaces; virtual reality; motor priming; motor imagery; neurofeedback; EEG

I. Introduction

Brain-Computer Interfaces (BCIs) are communication systems which translate user's brain activity into control commands. The most common signal acquisition is by using electroencephalography (EEG) [1]. This unique type of interfacing of humans with computers is proven useful in a wide range of applications for assistive, rehabilitative use, or entertainment. Most notably in the use by disabled users with paralysis or severe neuromuscular disorders [1], for restoration of active movement [2], in human-computer interaction research [3], and in virtual reality and video games [4].

In the particular case of stroke rehabilitation, BCIs have been mostly used with two different strategies. The first aims at bypassing non-functional corticospinal pathways for controlling robotic prosthetics [5], and the second aims at mobilizing neuroplastic changes in order to achieve the reorganization of motor networks and enhance motor recovery [6]. For the latter case, motor imagery (MI) BCI training (based on visuo-motor imagination) has been the most widely used BCI paradigm in research [7]. Results from previous studies have proven mental practice of action to be useful in MI-BCI [8]. Beneficial effects in motor control have been shown [9], and new paradigms have been proposed to maximize the recruitment of motor networks [10]. In stroke rehabilitation, the combination of BCIs with virtual environments has gained popularity, and it has been proven very useful to train functional upper limb pointing movements [11], [12]. Unfortunately, MI-BCI studies for stroke rehabilitation are very different in terms of (a) experimental design and (b) research protocols. So far in MI training, the use of unidirectional arrows is the most widely used visual feedback mechanism. Although there is no direct evidence that different feedback designs, i.e. realistic grasping with a hand vs. extending arrows, imply differences in performance in MI [13], previous studies have shown that the type of feedback can have different effects based on the learner [14]. For instance, emotional feedback (in the form of smiley faces) has shown positive results in MI performance [15]. In another experiment, displaying real-time cortical activity as neurofeedback was shown to significantly increase MI performance [16]. Furthermore, videogames and Virtual Reality (VR) feedback has also shown positive results, offering a more compelling experience to the user through 3D environments [4][17].

Despite the increased attention that BCI technology had with the launch of low-cost commercial EEG devices in the last few years, BCI technology is hardly used outside laboratory environments [17]. This is mainly due to the fact that current BCI systems lack reliability and good performance in comparison to other types of interfaces [18]. For instance, MI-BCI requires long training trials per session and settings are subject specific. As consequence, long and repetitive training sessions can result in user fatigue and declining performance over time. In addition, prolonged training is problematic in generating EEG oscillatory rhythms modulated during MI, such as mu (μ) and beta (β) rhythms [19]. Therefore, it is essential to identify what the key ingredients are for a successful MI-BCI training using specific criteria for motor rehabilitation.

New findings in MI experimentation have shown that increased vividness of imagery is strongly associated with the neural activity in motor related areas [20], but there is a limited understanding on how these factors affect the activity patterns of motor related areas. In fact, some studies have shown that physical activity prior to a MI task (motor priming) facilitates the engagement of motor networks on the subsequent MI task [21]. However, these studies were in a different context and it is not clear how they can affect the design of a MI-BCI paradigm. Further, some researchers have studied the effect of alternative feedback modalities on a BCI task, such as haptic and auditory feedback, with inconclusive results [22], [23]. Interestingly, it has been shown that the combination of audio and visual feedback decreases BCI performance, whereas the combination of haptic and visual feedback increases the performance [24], [25]. Finally, there is evidence that the kinesthetic imagination of movement is preferable over just visual imagination, resulting in increased MI-BCI performance [26].

In order to overcome the current limitations and improve MI-BCI based motor rehabilitation paradigms, we have developed a novel prototype that makes use of multimodal feedback, in an immersive VR environment delivered through a Head Mounted Display (HMD), integrated in a MI-BCI motor training task. Subsequently we designed, assessed and compared 3 MI-BCI neurofeedback paradigms based on the following criteria: 1) to improve user performance, and 2) to maximize the engagement of sensory-motor networks in the MI-BCI task. We studied the role of motor priming and of multimodal VR feedback compared to a control MI-BCI setting using the standard feedback provided by bars and arrows.

II. Methodology

A. BCI Training Task Design

A recent attempt to systematically identify all current flaws in BCI training protocols has proposed a set of desirable properties at three different levels – "Feedback", "Instructions", and "Tasks" – for a good instructional BCI design [17]. These suggestions are based on a methodological analysis, although without a formal validation. We have incorporated those guidelines in our BCI training protocol. In particular, we implemented them in the following way:

Feedback level:

1. Feeling of competence: we present only positive reinforcement.

2. Clear and meaningful feedback: we designed a simple task with visual and auditory feedback.

3. Explanatory and specific: clear self-explanatory goal oriented task.

4. Feedback that has a gap between current and desired performance: changes in VR show progress in achieving the goal.

5. Multimodal: use of hand tracking, HMD, and audio.

6. Engaging environment: we developed a realistic 3D virtual environment with the use of HMD.

Instructions level:

1. Goals are clearly defined: simplified and intuitive task.

2. The meaning of the feedback is explained: through briefing before each task.

3. The skill to be learned has been demonstrated: we demonstrated the training paradigm before each session.

Task level:

1. The task is challenging but still achievable: the task implemented standard settings used successfully in previous research.

2. The use of motivation and positive emotions through task specific mechanisms in a VR environment: through goal achievement in VR

B. Experimental Design

The experimental protocol consisted of 3 training conditions which users were exposed in a randomized order (VR-MP: Virtual Reality-Motor Priming, VR: Virtual Reality, and a Control Condition: Standard Motor Imagery), in a time-span of 3 days (1 condition per day). Each condition included 3 main stages: (1) subjects were first exposed to a 8 minute MI-BCI calibration session [see Figure 1 (a), (c)] followed by a 15 minute pause; (2) a MI-BCI session of 8 minutes [see Figure 1 (b), (d)] followed the calibration session; and (3) at the end of the MI-BCI session a set of self-report questionnaires were asked. In total, each condition took about 50 minutes. During all sessions in all conditions, EEG data were logged synchronously, time-stamped, including the

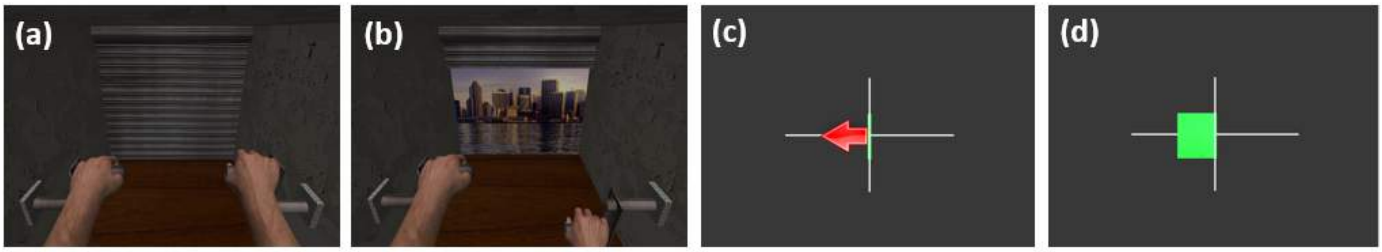

Figure 1. The two types of visual feedback: (a) VR feedback with the virtual representation of the users arms grasping the control handles for opening a garage door, (b) the virtual arms in task execution during observation or online control, (c) traditional arrow feedback prompting the user for motor imagery, (d) progress bar feedback on successful classification.

different stimulation codes.

1) Condition VR-MP: Multimodal Virtual Reality-Motor Priming

In this condition users were asked to carry out a previous motor execution for 8 minutes using an immersive virtual reality environment [see Figure 2(a)]. The combination between a VR headset (Oculus Rift) and a natural gesture interaction device (Leap Motion) enabled a simple interaction using their hands within a virtual environment. The motor activity involved the rotation of a virtual lever through circular movements for opening a big garage door. The virtual environment included mechanical sounds related with the movement of the door and the lever. Before each repetition, the user was informed of which hand should be used to open the garage door. A total of 20 repetitions with each hand were executed for the users at this stage. Each repetition consisted in approximately 4 seconds of motor execution using only one hand followed by a 2 second pause. This stage will be further referred as motor priming (MP) session. In the MI-BCI calibration session, the same VR task and feedback was used to support MI. In the MI-BCI the user had to imagine the same movement performed in the MP. Finally, the same virtual environment was used for the MI-BCI online session, in which the user could control the virtual arms through the BCI interface using MI.

2) Condition VR: Multimodal Virtual Reality

In this condition users were asked to carry out the MI-BCI calibration and online session, as in the previous condition, but without any prior MP [see Figure 2(b)].

3) Control Condition: Standard Motor Imagery

This condition followed the same protocol as the VR condition, but without the VR component. In this condition a standard MI-BCI setup was used, providing a “control” condition for the other conditions to be compared with. Here, simple bar and arrow elements without sounds (Graz visualization) were used as feedback mechanisms. Nevertheless, the MI task consisted in the motor imagery of the same upper-limb movements as described in conditions VR-MP and VR.

C. Experimental Setup

The experimental setup was composed by a desktop computer (OS: Windows 8.1, CPU: Intel® Core™ i5-4440 at 3.3 GHz, RAM: 8GB DDR3 1600MHZ, Graphics: Nvidia GT 630 1GB GDDR3), running the VR MI-BCI training task developed with the Unity 3D game engine (Unity Technologies, San Francisco, USA). For hand and finger tracking during motor priming, the Leap Motion controller (Leap Motion, Inc., San Francisco, California, United States) was used together with the Oculus Rift DK1 Head Mounted Display (HMD) (Oculus VR, Irvine, California, United States) and a stereo headset.

The BCI set up consisted of 8 active electrodes equipped with a low-noise biosignals amplifier and a 16-bit A/D converter at 256 Hz (g.MOBIlab biosignal amplifier, gtec, Graz, Austria). The spatial distribution of the electrodes followed the 10-20 system configuration with the following electrodes over the sensory-motor areas: FC3, FC4, C3, C4, C5, C6, CP3, and CP4. The signal amplifier was connected via bluetooth to a laptop computer (CPU: Intel® Core™ i3-3217U at 1.80 GHz, RAM: 8GB DDR3 1600MHZ, Graphics: Intel® HD Graphics 4000) for the EEG signal acquisition and processing through the OpenVibe platform [27]. For all conditions, a Common Spatial Patterns (CSP) filter was used for feature extraction, which has been shown to deliver better performance in MI experiments [28], and a Linear Discriminant Analysis (LDA) for the classification of MI from EEG data. Finally, the data from OpenVibe were transmitted to the RehabNet Control Panel (RehabNetCP) [29] through the VRPN protocol [30] to control the virtual environment. The RehabNet Control Panel is a free tool that acts as a device router to bridge a multiple interfaces with virtual environments.

D. Participants

The study consisted of a total of 9 healthy participants (8 male, 1 female) with a mean age of 27 ± 2 years old. Participants were recruited based on their motivation to participate in the study, with no previous known neurological disorder, and no previous experience in BCIs. All participants were students and staff from the University of Madeira and were recruited at the Madeira Interactive Technologies Institute. All participants signed an informed consent form before participation.

Figure 2. Virtual Reality-Motor Priming (VR-MP) condition. (a) Motor priming using the Leap Motion controller and an immersive VR. (b) Motor imagery feedback.

E. Questionnaires

Subjective experience was gathered through three questionnaires: the Presence Questionnaire, the Vividness of Movement Imagery Questionnaire-2, and the NASA TLX. The Presence Questionnaire (PQ) is a tool that measures the degree to which individuals experience presence in a virtual environment and the influence of possible contributing factors to the intensity of the experience [31]. PQ has 24 questions in a seven-point Likert scale to assess items such as realism, possibility to act and sounds. Items related to haptic assessment were excluded because this aspect was not addressed in our experiment. Vividness of Movement Imagery Questionnaire-2 (VMIQ2) [32] was used to assess the kinesthetic imagery ability of the participant. The VMIQ [33] has been previously used to determine differences in neural activation patterns between vivid and non-vivid imagery. Finally, the NASA TLX questionnaire was used to measure task load through a number of subscales [34]. These subscales include Mental Demands, Physical Demands, Temporal Demands, Performance, Effort and Frustration.

F. Power Spectral Density Estimation

EEG data were processed extracting the Power Spectral Density (PSD) of the signals in Matlab (MathWorks Inc., Massachusetts, US). The power was extracted every 500 ms using Welch's method with windows of 128 samples for the following frequency bands: alpha (8 Hz -12 Hz), beta (12 Hz-30 Hz), theta (4 Hz- 7 Hz), and gamma (25 Hz- 100 Hz). For the current analysis and because we were only measuring from sensory-motor areas, data were averaged for all the channels for each experimental condition. In order to remove major artifacts related with eye blinking and muscular activity, a manual component rejection process was carried out using Independent Component Analysis (ICA) with the help of the EEGLAB toolbox [35].

III. Results

In this experiment we wanted to understand how to improve user performance and maximize the engagement of sensory-motor networks in a MI-BCI motor rehabilitation task. Therefore, we studied the role of motor priming and multimodal VR feedback compared to a control MI-BCI setting.

A. Do different conditions improve MI-BCI training performance?

From the MI-BCI calibration session (see Figure 3), we can observe that the multimodal setup with motor priming condition (VR-MP) provides the highest performance

MI-BCI Calibration Performance

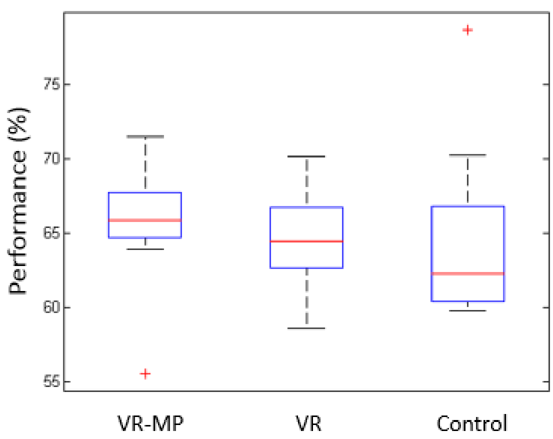

Figure 3. MI-BCI calibration performance for the 3 experimental conditions (VR-MP, VR-MI, Control)

(*M*=65.6%, *SD*=4.3) when compared with the VR only condition (*M*=64.65%, *SD*=3.6) and the control condition with the traditional feedback (*M*=64.62%, *SD*=6.2). Although there is no statistical difference due to the small sample size and large user variability, these data suggest a benefit of both VR and VR-MP conditions over the traditional MI-BCI training.

B. Is subjective experience modulated by condition?

Through an Analysis of Variance (ANOVA) we found a significant difference between condition VR-MP and Control for the total score of the TLX questionnaire. The reported workload is higher for the VR-MP condition (*M*=17.556, *SE*=3.575, p<0.001). More specifically, we found differences for mental demand (*M*=12, *SD*=5, p<0.05), temporal demand (*M*=7, *SD*=3, p<0.05)), and frustration (*M*=11, *SD*=4, p<0.05)) (see Figure 4). Interestingly, we could see that physical demand (*M*=7, *SD*=5), performance (*M*=10, *SD*=4) and effort (*M*=12, *SD*=4) were not modulated by condition despite the fact that condition VR-MP includes an additional motor component.

The Kinesthetic Imagery assessment with the VMIQ-2 questionnaire revealed an average ability of 61.36% ± 12. The cut-off-point established by Whetstone [36] estimates good imagery ability with a total score of 70 %. Three of our subjects had good ability and four displayed lower imagery ability. When comparing the outcome of the VMIQ2 among conditions, we observe that conditions did not affect the participant's ability to create clear and vivid motor imagery, showing consistent reports after each condition.

TLX Questions

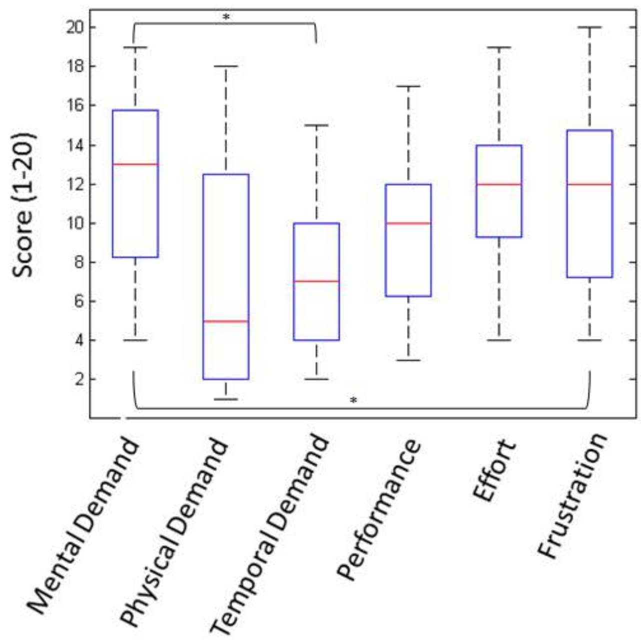

Figure 4. Mean responses of TLX questionnaire in the domains of Mental Demand, Temporal demand, frustration physical demand, performance, and Effort. Significant differences between conditions (p < 0.05) are indicated with *.

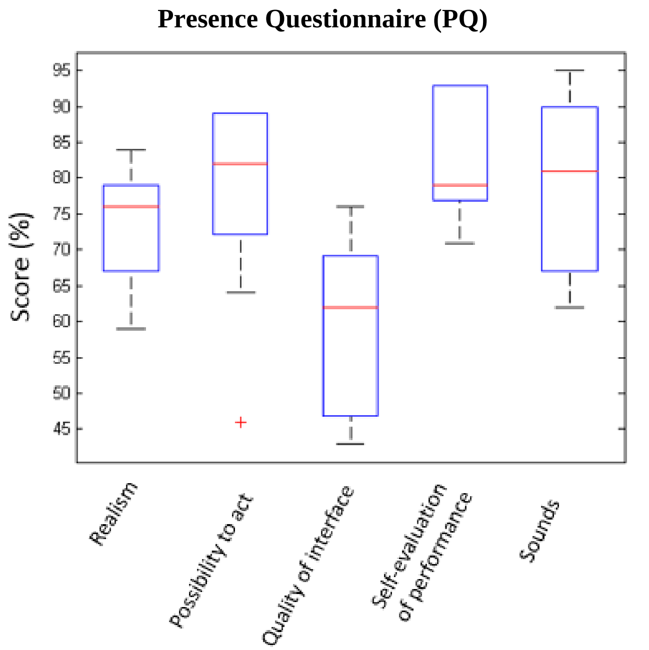

Figure 5. Presence questionnaire self-report on the perceived sense of presence during BCI during the multimodal VR condition with motor priming (VR-MP).

C. *How realistic was the multimodal VR simulation?*

The score of the Presence Questionnaire indicates an overall acceptance of the VR task (see Figure 6). Overall, four out of the five assessed domains scored above the 70% threshold: realism (*M*=73%, *SD*=8), the possibility to act through initiated actions and events (*M*=77%, *SD*=14), sounds of the VR task (*M*=79%, *SD*=12), and the self-evaluation of performance, which had the highest score (*M*=83%, *SD*=9). The quality of the interface was the lowest score (*M*=58%, *SD*=13), which was due to the technical limitations of the Leap Motion tracking in terms of field of view and accuracy. However, the reports indicate that the interface did not affect the perceived performance and realism of the VR task. Finally, we found a low and not significant correlation between the PQ self-evaluation report on performance and the actual MI-BCI performance (r= 0.2255, p=0.5596).

D. *Do conditions modulate brain activity patterns?*

A repeated-measures ANOVA was carried out for each EEG frequency band and we found a modulation of EEG rhythms in all conditions (alpha: $F(2, 15.03) = 5.99$, $p < .05$; beta: $F(2, 9.23) = 7.33$, $p < .05$; theta: $F(2, 13.19) = 4.61$, $p < .05$; low-gamma: $F(2, 13.19) = 4.61$, $p < .05$; and high-gamma: $F(2, 8.89) = 5.95$, $p < .05$) (see Figure 5). Pairwise comparisons revealed that the alpha band power was significantly greater in the VR-MP condition compared with Control ($p < 0.01$). Consistent results were also found for the Theta band ($p < 0.05$), Low-Gamma band ($p < 0.05$), and High Gamma band ($p < 0.05$). Additionally, for the Beta band data revealed that both VR conditions had an increased activity: VR-MP vs. Control ($p < 0.01$), and VR vs. Control ($p < 0.05$).

E. *Relationship between subjective experience and brain activity.*

In order to assess the relationship between subjective experience – as reported through the questionnaires – and the elicited brain activity patterns, we decided to use a stepwise multilinear regression modelling approach. With this model we can determine statistical relationships between the generated EEG rhythms during the MI-BCI conditions (alpha, beta, theta, and gamma bands) and the answers of the questionnaires (TLX, PQ, and Kinaesthetic Imagery). Table 1 summarizes the findings of the model, including only the significant contributions. From TLX, we can see that Mental Demand (Coeff. = 1.0977, p<0.05) and Temporal Demand (Coeff. = 0.9137, p<0.05) contribute to increased Alpha activity. Effort (Coeff. = 0.695, p<0.05), Frustration (Coeff. = 0.7427, p<0.05), and Physical Demand (Coeff. = 1.6197, p<0.05) with increased Theta activity, as well as Physical Demand contributes to a reduced Gamma activity (Coeff. -

Table 1. Multi-linear stepwise regression model. The table shows the coefficients of the significant contribution in the regression model.

EEG Rhythms / Subjective Self-Reports	Alpha	Beta	Theta	Gamma
TLX: Mental Demand	**1.0977**	-	-	-
TLX: Temporal Demand	**0.9137**	-	-	-
TLX: Effort	-	-	**0.695**	-
TLX: Frustration	-	-	**0.7427**	-
TLX: Physical Demand	-	-	**1.6197**	**-0.5942**
PQ: Quality of Interface	-	-	**1.1567**	-
PQ: Realism	-	-	-	**-1.4617**
PQ: Sounds	-	-	-	**-0.9195**
Kinaesthetic Imagery	-	**2.697**	**-2.463**	-

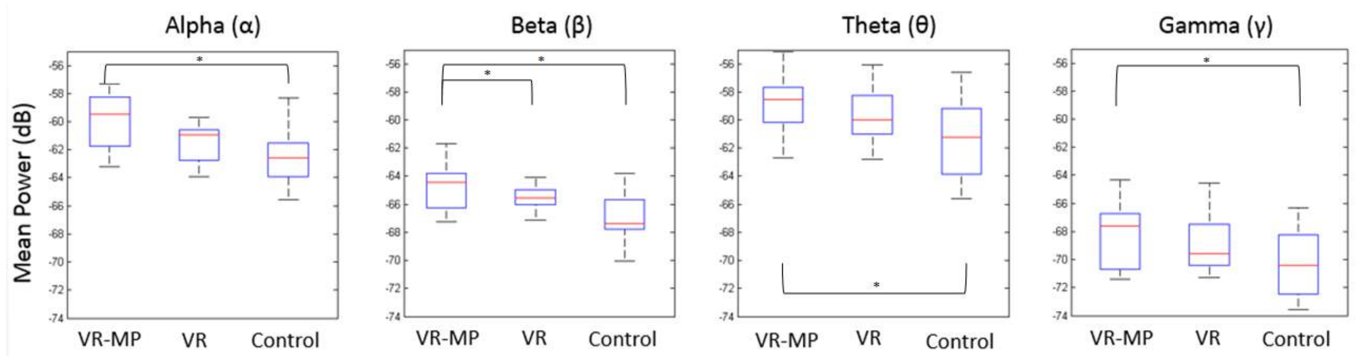

Figure 6. Brain activity patterns per experimental condition divided in the alpha (8 Hz -12 Hz), beta (12 Hz- 30 Hz), theta (4 Hz- 7 Hz), gamma (25 Hz- 100 Hz) frequency bands. Significant differences (p < 0.05) are indicated with *.

0.5942, $p<0.05$). From PQ, Quality of Interface contributes to the activation of the Theta band (Coeff. = 1.1567, $p<0.05$), and Realism (Coeff. = -1.4617, $p<0.05$) and Sounds (Coeff. = -0.9195, $p<0.05$) to a reduced activity in the Gamma band. Finally, we can observe that there is a relationship between the ability of kinaesthetic imagery with a higher activation of the Beta band (Coeff. = 2.697, $p<0.05$) – which is known to be related with the sensory-motor rhythms generated during MI [37] – and reduced Theta activity (Coeff. = -2.463, $p<0.05$).

IV. Discussion

The obtained results show interesting findings in several dimensions related with the use of MI-BCI for neurorehabilitation. Firstly, the accuracy of the MI-BCI calibration revealed higher performances in the VR-MP condition and in the VR condition alone than in the standard setup. Although the sample size is limited (9 users x 3 conditions each) and differences are not significant, these results show a trend suggesting that the addition of multimodal VR feedback and of motor priming could increase the performance of MI-BCI training that uses with simple 2D arrows and bars.

Secondly, the reported task load (TLX questionnaire) shows a clear difference in the workload reported between the VR-MP and Control conditions. Although in the VR-MP condition the user had to exert more physical activity, the physical demand and effort subdomains of the TLX were not affected. Therefore, we can argue that the inclusion of the motor priming component with an immersive VR environment turned the MI-BCI into a more mentally demanding task with the potential of engaging additional neural circuits than in the other 2 conditions. This hypothesis is also supported by the differences found in the EEG activity patterns. Additionally, although we find no differences in the kinesthetic imagery assessment after each condition, we do find a correlation between the values reported by the users and their capacity to display enhanced activity in the Beta band, which is related with the generation of the sensory-motor rhythms. Thus, the use of the vividness questionnaire could play an important role as inclusion criteria in the neurorehabilitation through MI-BCI paradigms. Nevertheless, these questionnaires are quite general causing the necessity to create kinesthetic imagery questionnaires more specific for upper limb goal-oriented motor imagery. Finally, the PQ shows high scores in four out of the five domains, demonstrating that important factors, such as realism and the self-evaluation of performance, were covered successfully in our multimodal VR immersive system. Additionally, although the arm tracking device did not affect the quality of the experience, the interaction through the Leap Motion sensor can be improved.

With regards to the brain activity patterns, we studied the EEG rhythms for each condition. Results revealed significant contributions of the VR-MP condition to the engagement of alpha and beta bands, which are more related with MI practice. This modulation becomes very relevant for the design of new BCI-MI tools when the final goal is to restore motor function by mobilizing cortical plasticity by means of increased cortical activation in the affected somatosensory and motor areas.

In the future we plan to further extend this study with more participants and a more homogenous target population, this time considering stroke patients as well. Our ultimate goal is to clinically validate the VR-MP approach in a longitudinal MI-BCI study with stroke patients.

Acknowledgment

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