NeuRow: An Immersive VR Environment for Motor-Imagery Training with the Use of Brain-Computer Interfaces and Vibrotactile Feedback

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Abstract: Motor-Imagery offers a solid foundation for the development of Brain-Computer Interfaces (BCIs), capable of direct brain-to-computer communication but also effective in alleviating neurological impairments. The fusion of BCIs with Virtual Reality (VR) allowed the enhancement of the field of virtual rehabilitation by including patients with low-level of motor control with limited access to treatment. BCI-VR technology has pushed research towards finding new solutions for better and reliable BCI control. Based on our previous work, we have developed NeuRow, a novel multiplatform prototype that makes use of multimodal feedback in an immersive VR environment delivered through a state-of-the-art Head Mounted Display (HMD). In this article we present the system design and development, including important features for creating a closed neurofeedback loop in an implicit manner, and preliminary data on user performance and user acceptance of the system.

1 INTRODUCTION

Motor Imagery (MI) is the mental rehearsal of movement -without any muscle activation- and is a mental ability strongly related to the body or 'embodied' cognition (Hanakawa, 2015). MI appears to largely share the control mechanisms and neural substrates of actual movement both in action execution and action observation (Eaves et al., 2014), providing a unique opportunity to study neural control of movement in either healthy people or patients (Mulder, 2007; Neuper et al., 2009). Since MI leads to the activation of overlapping brain areas with actual movement, and because sensory and motor cortices can dynamically reorganize (Lledo et al., 2006; Rossini et al., 2003), MI constitutes an important component for motor learning and recovery. Hence, MI has important benefits and is currently utilized as a technique in neurorehabilitation for people with neurological impairments (Dickstein et al., 2013).

MI offers an important basis for the development of brain-to-computer communication systems called Brain–Computer Interfaces (BCIs). BCIs are capable of establishing an alternative pathway between the brain and a computer or prosthetic devices (Wolpaw et al., 2002) that could assist (assistive BCI) or rehabilitate physically (restorative BCI) disabled people and stroke survivors (Dobkin, 2007).

More recently, Virtual Reality (VR) feedback has also been used in MI BCI training, offering a more compelling experience to the user through 3D virtual environments (Lotte et al., 2013a). The fusion of BCI and VR (BCI-VR) allows a wide range of experiences where participants can control various aspects of their environment -either in an explicit or implicit manner-, by using mental imagery alone (Friedman, 2015). This direct brain-to-VR communication can induce illusions mostly relying on the sensorimotor contingencies between perception and action (Slater, 2009).

The idea of utilising BCIs in virtual rehabilitation (virtual reality and tele-medicine for neurorehabilitation), was fostered in order to complement current VR rehabilitation strategies (Bermudez i Badia and Cameirao, 2012; Lange et al.,

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2012) where patients with low level of motor control –such as those suffering of flaccidity or increased levels of spasticity (Trompetto et al., 2014)- could not benefit due to low range of motion, pain, fatique, etc.

The main challenge in the use of BCIs, regardless of the BCI cost, lies in the lack of reliability and good performance at the system level that inexperienced users have (Vourvopoulos and Bermúdez i Badia, 2016) due to BCI "illiteracy" of users (inability of the user to produce vivid mental images of movement resulting in poor BCI performance) (Allison and Neuper, 2010; Vidaurre and Blankertz, 2009). Although previous studies have shown mixed results, the combination of haptic and visual feedback seems to increase the performance (Gomez-Rodriguez et al., 2011; Hinterberger et al., 2004). It has been shown that replacing the standard visual BCI feedback with vibrotactile feedback does not interfere with the EEG signal acquisition (Leeb et al., 2013) and also does not impact negatively the classification performance (Cincotti et al., 2007; Leeb et al., 2013). On the other hand, it has been shown to have a positive effect on visual workload measured in a multiple object tracking task (MOT) where the data revealed significant differences between visual or tactile feedback (Gwak et al., 2014). It has also been shown that with the use of haptic feedback, the user cam pay more attention to the task instead of to the feedback (Cincotti et al., 2007), and in (Jeunet et al., 2015) users achieved higher scores in the vibrotactile feedback setting. Vibrotactile feedback has also been used in a hybrid BCI system (Yao et al., 2014), where MI with selective sensation (SS) were used in order to increase performance. On this system, equal vibration is applied to both wrists of the user and he/she has to imagine that the vibration to one of the sides is stronger than the other (SS). SS combined with MI increased the overall performance of the system. In (Jeunet et al., 2015), it is also reported that the vibrotactile feedback applied on the user's hand significantly increases MI performance. In (Leonardis et al., 2012) the use of vibrotactile feedback directly applied to certain tendons is used to convey the illusion of movement to the user, and in conjunction with a virtual representation of the arm, significantly increased the accuracy of a BCI system. Further, recent findings with the use of virtual arms have shown that the combination of motor priming (physical rehearsal of a movement) preceding BCI-VR MI training can improve performance as well as the capacity to modulate and enhance sensorimotor brain activity rhythms, important in rehabilitation research (Vourvopoulos et al., 2015).

In addition, there is an increased need for alternative motivational mechanisms and feedback approaches for BCI systems (Lotte, 2012; Lotte et al., 2013b). Previous research in learning, states that a poorly designed feedback can actually deteriorate motivation and impede successful learning (Shute, 2008) while providing extensive feedback to the user can lead to efficient and high quality learning (Hattie and Timperley, 2007). Lotte et al. recommended a set of guidelines for a good instructional design in BCI training, in which (1) the user should only be presented with the correct classified action for enhancing the feeling of competence; (2) provide a simplified and intuitive task; (3) meaningful and self-explanatory task; (4) challenging but achievable, with feedback on progress of achievement; and finally (5) in an engaging 3D virtual environment (Lotte et al., 2013b).

To date, and to the best of our knowledge, there is not a holistic approach in BCI MI training that combines the advantages of different feedback modalities (immersive VR environment, vibrotactile feedback), training aproaches (motor priming preceding motor observation) and motivational mechanisms (game-like tasks). Further, in order to be able to harness the benefits of BCI in neurorehabilitation, two questions need to be addressed: (a) how can we increase user performance in BCI MI training, and (b) how can we maximize the activation of the brain areas responsible for actual movement. Answering these questions will enable the appearance of novel BCI paradigms that will allow us to promote more efficiently reorganization of sensorimotor cortices of motor impaired patients (such as for instance stroke), which ultimately can lead to higher levels of recovery.

In this paper we describe the development and pilot assessment of NeuRow, a novel BCI-VR environment for MI training. NeuRow makes use of multimodal feedback (auditory, haptic and visual) in a VR environment delivered through an immersive Head Mounted Display (HMD), integrated in a BCI MI training task (left | right hand motor imagery).

Finally, NeuRow is available for different platforms and is accessible for free at http://neurorehabilitation.m-iti.org/bci/.

2 METHODOLOGY

2.1 Experimental Setup

The experimental setup was composed by a desktop computer (OS: Windows 8.1, CPU: Intel® Core™ i5-2400 at 3.10 GHz, RAM: 4GB DDR3 1600MHZ, Graphics: AMD Radeon HD 6700), running the acquisition software, the BCI-VR task, HMD, EEG system, and a vibrotactile module.

2.1.1 EEG Acquisition

The BCI system consisted of 8 active electrodes equipped with a low-noise biosignal amplifier and a 16-bit A/D converter at 256 Hz (g.MOBIlab+ biosignal amplifier, g.tec, Graz, Austria). The spatial distribution of the electrodes followed the 10-20 system configuration (Klem et al., 1999) with the following electrodes over the somatosensory and motor areas: Frontal-Central (FC5, FC6), Central (C1, C2, C3, C4), and Central-Parietal (CP5, CP6) (Figure 1 a). The signal amplifier was connected via bluetooth to the desktop computer for the EEG signal acquisition. EEG data acquisition and processing was performed through the OpenVibe platform (Renard et al., 2010). Finally, the data from OpenVibe was transmitted to the RehabNet Control Panel (Reh@Panel) (Vourvopoulos et al., 2013) via the VRPN protocol (Taylor et al., 2001) to control the virtual environment. The RehabNet Control Panel is a free tool that acts as a middleware between multiple interfaces and virtual environments.

2.1.2 Feedback Presentation

For delivering feedback to the user, the Oculus Rift DK1 HMD was used (Oculus VR, Irvine, California, USA). The HMD is made of one 7" 1280x800 60 Hz LCD display (640x800 resolution per eye), one aspheric acrylic lens per eye, 110° Field of View (FOV), internal tracking through a gyroscope, accelerometer, and magnetometer, with a tracking frequency of 1000Hz (Figure 1 b).

2.1.3 Vibrotactile Feedback

A custom vibrotactile feedback module was developed with out-of-the-box components including an Arduino Mega 2560 board and vibrating motors. The vibrating motors (10mm diameter, 2.7mm thick) performed at 11000 RPM at 5V and were mounted on cylindrical tubes that acted as grasping objects for inducing the illusion of movement during the BCI task (Figure 1 c). In our setup, a pair of carton-based tubes with 12cm of length and 3cm diameter were used. Finally, 3D printed cases were produced to accommodate the vibrating motors inside the tubes. All hardware and software blueprints are made available for free online.

2.2 BCI Task Design

2.2.1 BCI-VR Training Protocol

The training protocol was designed and adapted based on the Graz-BCI paradigm (Pfurtscheller et al., 2003), substituting the standard feedback presented (directional arrows) by multimodal VR feedback. The first step of the training consist on the acquisition of the raw EEG data in order to train a linear discriminant classifier to distinguish Right and Left imagined hand movements. Throughout the training session, the user has to perform mental imagery of the corresponding hand (based on the presented stimuli). For each hand, the user is stimulated both visually (VR action observation) and haptically through the vibration on the corresponding hand (Figure 2 a). The training session was configured to acquire data in 20 blocks (epochs) per class (Right or Left hand imagery) in a randomized order. Following the training, the data is used to compute a Common Spatial Patterns (CSP) filter, a spatial filter that maximizes the difference between the signals of the two classes. Finally, the raw EEG and the spatial filter are used to train a Linear Discriminant Analysis (LDA) classifier.

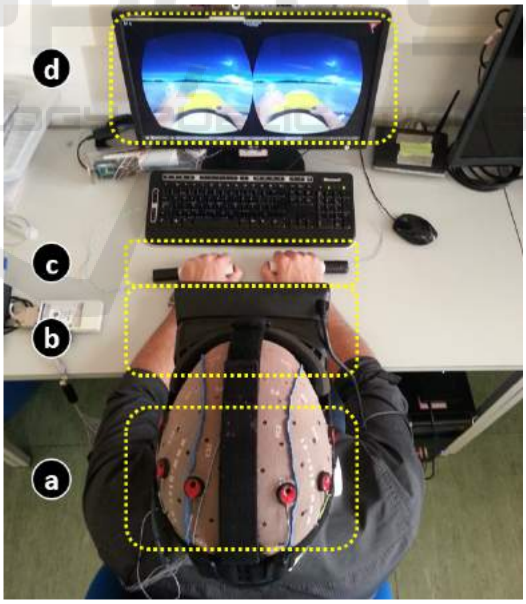

Figure 1: Experimental setup (a) EEG cap with 8 active electrodes, (b) HMD, (c) vibrotactile modules, (d) BCI feedback.

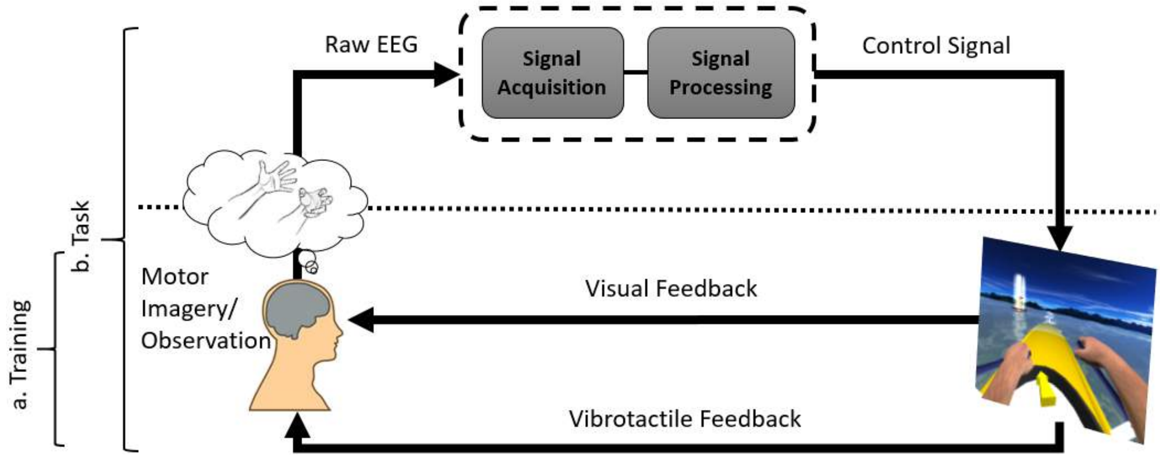

Figure 2: Neurofeedback loop. (a) During the training session, the user is performing in a randomized order MI combined with motor observation of the virtual hands rowing while vibrotactile feedback is delivered to the corresponding hand. (b) The user relies on MI alone in order to control the virtual hands in a closed-loop system after training.

2.2.2 BCI-VR Task

The BCI-VR task was designed based on literature and previous work, incorporating important features for a successful brain-to-computer interaction in terms of feedback, protocol design, and accessibility. The BCI-VR task involves boat rowing through mental imagery only with the goal of collecting as many flags as possible in a fixed amount of time. NeuRow is a self-paced BCI neurogame, meaning that is not event related, and the user controls the timing of rowing actions like he/she would do in real-life (Figure 2 b). NeuRow is a multiplatform virtual environment developed in Unity game engine (Unity Technologies, San Francisco, California, USA). Finally, NeuRow is optimized for different platforms, however with different features (Table 1). Namely:

- *Desktop*: The standalone version for PC, supports high quality graphics for an immersive VR experience with the support of the Oculus Rift DK1 headset, the Leap Motion hand controller (Motion control, San Francisco, California, USA) available for optional motor-priming before the MI BCI session. Finally, vibrotactile feedback is supported through the use of custom made hardware for controlling through USB up to 6 vibration motors. Data logging is supported for boat trajectory, target location, score and time.

- *Mobile*: The mobile version is built for Android OS devices, receiving data via the RehabNet UDP protocol through the Reh@panel. For phones, the VR feature is utilized for VR glasses (e.g. Google Cardboard) by applying lens correction for each eye, and using the phone gyroscope and magnetometer for head tracking, offering an immersive experience similar to the Oculus DK1 and DK2 HMDs.

- *Web browser*: The web version uses the Unity web player (compatible through Internet Explorer, Firefox or Opera), does not support the networking, HMD and haptic components due to security restrictions. Instead, the web NeuRow acquires data through emulated keyboard events generated by the Reh@panel.

The in-game interface is simple, with two high fidelity virtual arms to rotate the oars, time indication, score and navigational aids (Figure 3). NeuRow can be customized with different settings, depending on the experimental setup, BCI paradigm and running platform. Through the settings, one can chose if the session is part of MI training or self-paced online control session for navigation of the boat. During

Table 1: NeuRow features for the different supported platforms.

Features/ Platform	**Desktop**	**Android**	**Web**
Logging	✓	X	X
VR	✓ (Oculus)	✓ (Google Cardboard)	X
Hand Tracking	✓ (Leap Motion)	X	X
Networking	✓	✓	X
Platform Independent	X	X	✓
Vibrotactile Feedback	✓ (Arduino)	X	X

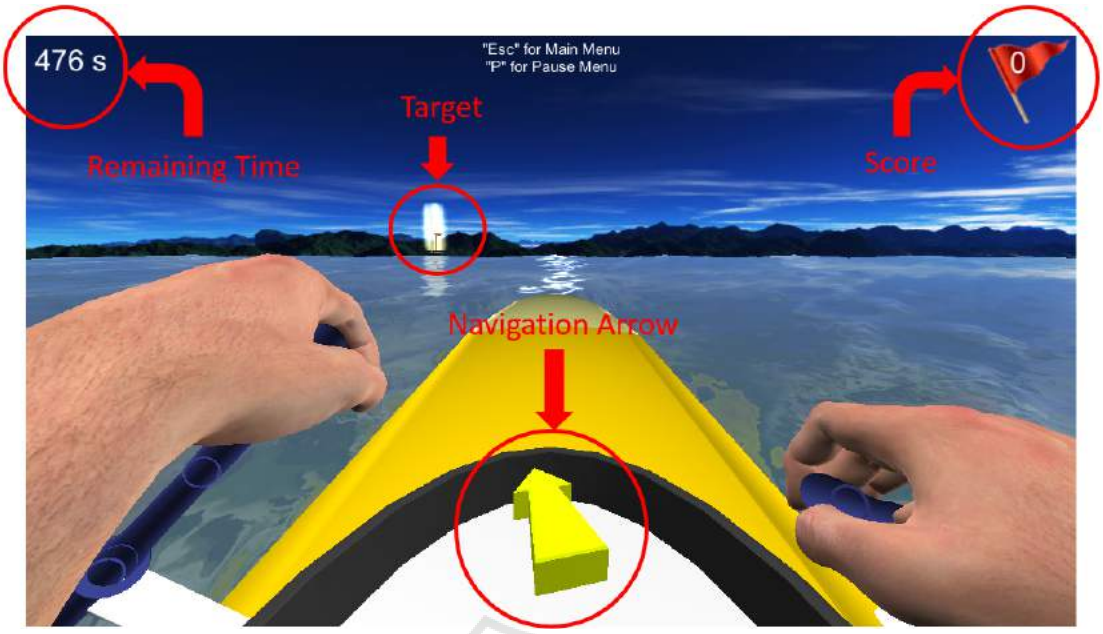

Figure 3: In-game interface. An arrow indicates the direction of the target and also the distance by changing its colour (red for far blending up to green for close). Top Left: Remaining time for the end of the session. Middle: A flag with a ray acts as the game targets, Top Right: Game scoring, counting the amount of targets.

training, the navigational arrow and the targets are removed to focus the user only on the multimodal MI BCI-VR task. During self-paced mode, the behaviour of the boat can be changed by setting the heading speed, turn speed and cut-off angle. The cut-off angle is the allowed angle that the boat can turn with respect to the target flag before stopping. This serves as a protection mechanism to help the player not to deviate in excess from the target.

2.3 Participants

A voluntary sample of 13 users (mean age of 28 ± 5 years old) was recruited for the pilot study, based on their motivation to participate in the study. All participants were male and right handed with no previous known neurological disorder, nor previous experience in BCIs. Participants were either university students or academic staff. Finally, all participants provided their written informed consent before participating in the study.

2.4 Questionnaires

Before each BCI training session, demographics and user data were gathered through the following questionnaires:

- The Vividness of Movement Imagery Questionnaire-2 (VMIQ2) was used to assess the capability of the participant to perform an imagined movement (Kinesthetic Imagery) (Roberts et al., 2008). Kinesthetic Imagery (KI) questions were combined with mental chronometry by measuring the response time in perceptual-motor tasks with the help of a timer.
- For assessing gaming experience we used the Gamer Dedication (GD) questionnaire, a 15 factor classification questionnaire in which participants are asked whether they "strongly disagree," or "strongly agree" with a series of statements about their gaming habits (Adams and Ip, n.d.).

After the BCI task, the following questionnaires were administered:

- The NASA TLX questionnaire was used to measure task load considering Mental Demand, Physical Demand, Temporal Demand, Performance, Effort and Frustration (Hart and Staveland, 1988).
- The core modules of the Game Experience Questionnaire (GEQ) were used at the end of the BCI session. GEQ assesses game experience using Immersion, Flow, Competence, Positive and Negative Affect, Tension, and Challenge (IJsselsteijn et al., 2008).
- The System Usability Scale (SUS) is a ten-item scale giving a global view of subjective assessments of usability (Brooke, 1996).

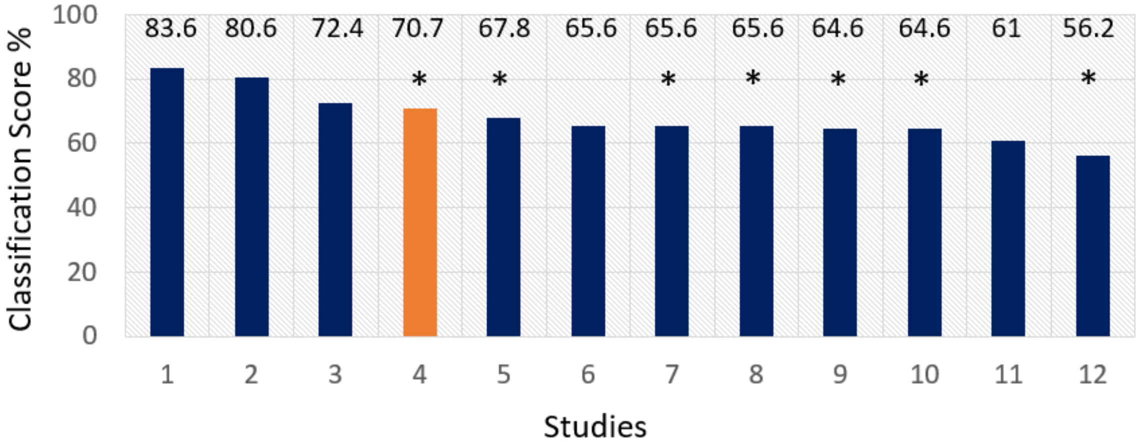

Figure 4: Ranked accuracy of performance in pure MI based BCI studies using two-classes (left and right hand imagery) with respect to LDA classification (Boostani and Moradi, 2004; Garcia et al., 2003; Obermaier et al., 2001; Solhjoo and Moradi, 2004). The asterisk (*) over 4,5,7,8,9,10 and 12 (Vourvopoulos et al., 2015; Vourvopoulos and Bermúdez i Badia, 2016) indicates studies which use the same feature extraction method (BP with CSP). The data of this study corresponds to the 4th best.

2.5 Data Analysis

2.5.1 Power Spectral Density (PSD)

EEG signals were processed in Matlab (MathWorks Inc., Massachusetts, US) with the EEGLAB toolbox (Delorme and Makeig, 2004) for extracting the Power Spectral Density (PSD). The power spectrum was extracted for the following frequency rhythms: Alpha (8 Hz - 12 Hz), Beta (12 Hz - 30 Hz), Theta (4 Hz - 7 Hz), and Gamma (25 Hz - 90 Hz). Independent Component Analysis (ICA) was used for removing major artefacts related with power-line noise, eye blinking, ECG and EMG activity. 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.

2.5.2 Engagement Index

The Engagement Index (EI) is a metric proposed at NASA Langley for evaluating operator engagement in automated tasks, was validated through a bio-cybernetic system for Adaptive Automation (Pope et al., 1995), and is widely used in EEG studies for assessing engagement (Berka et al., 2007). We therefore computed engagement index from the EEG power spectrum according to equation: EI = $\beta/(\alpha+\theta)$, where α = Alpha band, β = Beta band and θ = Theta band.

3 RESULTS

In the following section we analyse NeuRow's BCI task performance in terms of classifier score during training, user acceptance as assessed by the SUS, GEX and TLX questionnaires, and finally the relationship between game behaviour and user experience through the questionnaires and also the EEG activity.

3.1 Performance

Comparing the performance score with previous studies which used LDA classifiers in two class (left, right hand) MI, we are able to gain insights concerning the effectiveness of our BCI-VR paradigm in terms of user control (Boostani and Moradi, 2004; Garcia et al., 2003; Obermaier et al., 2001; Solhjoo and Moradi, 2004). As illustrated in Figure 4, the comparison places NeuRow as the fourth highest with a mean performance of 70.7% out of 12 studies. Moreover, of those studies that used exactly the same feature extraction technique of band power (BP) and CSP (Vourvopoulos et al., 2015; Vourvopoulos and Bermúdez i Badia, 2016), NeuRow scores the highest. Finally, of those studies that used VR as a training environment (Vourvopoulos et al., 2015), again NeuRow scores first.

3.2 User Acceptance

To assess different aspects of the user experience during online control of NeuRow, the mental workload, gaming experience and system usability were assessed after the task.

For workload, the NASA-TLX mean score was relatively high at 66.8/100 (*SD = 14.5*). As it is illustrated in Figure 5, the two lowest scores are those for physical (*M = 4.4, SD = 3.4*) and temporal (*M = 6.5, SD = 3*) demand. The highest score is on effort (*M = 16.4, SD = 5.2*) followed closely by frustration (*M = 13.3, SD = 5.2*) and mental demand (*M = 12.8, SD = 5*). Performance lies in the middle (*M = 11.4, SD = 6.2*).

From the GEQ, we extracted seven domains based on the sub-scale scoring. The highest score is in flow (*M = 3.1, SD = 0.4*) followed by immersion (*M = 2.8, SD = 0.4*) and positive affect (*M = 2.8, SD = 0.7*). A moderate score is achieved on tension/annoyance (*M = 2.5, SD = 0.9*) and challenge (*M = 2.5, SD = 0.5*). Finally, competence (*M = 1.8, SD = 0.7*) and negative affect scored the lowest (Figure 6).

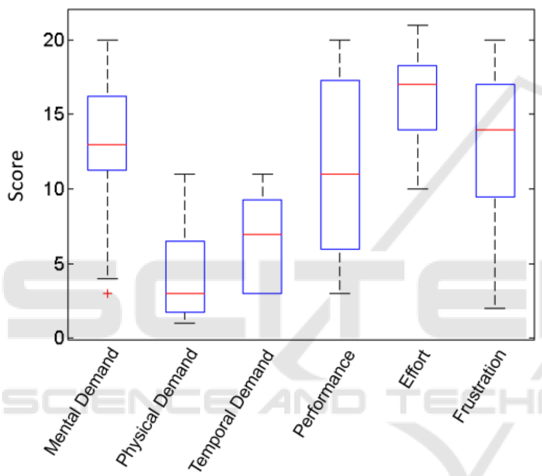

Figure 5: TLX scores between 1-20 for mental demand, physical demand, temporal demand, performance, effort and frustration.

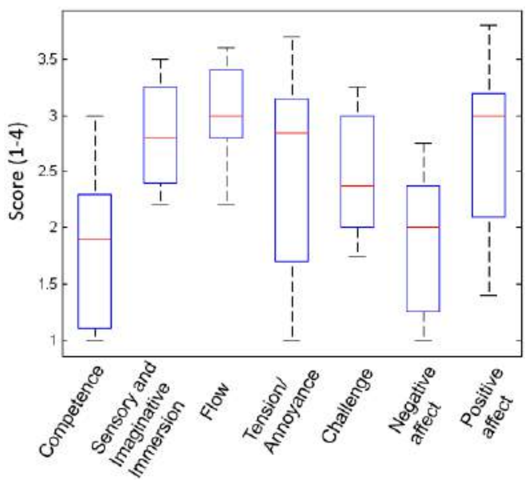

Figure 6: Scores for the GEQ core questionnaire domains.

The system usability assessed by the SUS scored a mean of 74 (*SD = 7.2*). Based on the SUS rating scale (Figure 7), our system is classified as "Good" and it is within the acceptability range (Bangor et al., 2009).

3.3 User-Profile and in-Game Behaviour

By assessing the relationship of the reported experience and the EEG activity with the in-game behaviour (score, distance, speed, trajectory) we

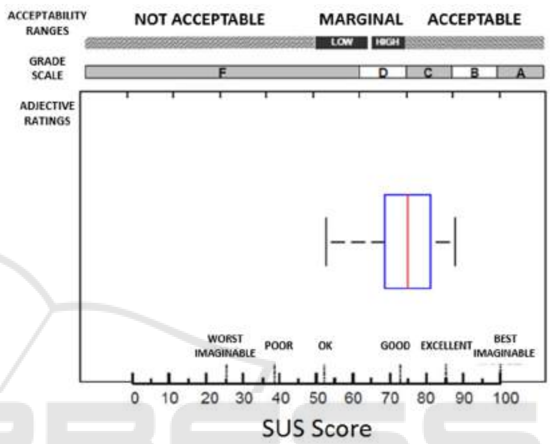

Figure 7: SUS results for all users. Acceptability scales are displayed on top (not acceptable, marginal and acceptable), followed by the grade scale (A to F) and the adjective rating (0-100).

Table 2: Correlation table between reported experience, extracted EEG bands and in-game behaviour.

	Distance	Speed	Score	Smoothness
TLX: Total	-.695	-.699	-.697	
TLX: Performance	-.595	-.599		
TLX: Frustration	-.728	-.737	-.686	
Mental Chronometry	.618	.615	.728	
Alpha band	-.611	-.607		
Theta band	-.672	-.670		
Engagement Index	-.770	-.768	-.649	-.595

identified a set of correlations. As illustrated in Table 2, the total workload correlates with distance, speed and score. In addition, two TLX sub-domains have correlations. Performance is significantly correlated with distance and speed, as well as frustration is significantly correlated with distance, speed and score. Furthermore, mental chronometry (the response time in perceptual-motor tasks), significantly correlates with distance, speed and score. Finally, from the extracted EEG bands and the resulting Engagement Index, we can see that Alpha and Theta bands are reversely correlated with distance and speed. Finally, Engagement Index is interestingly correlated with all in-game metrics. In particular for distance, speed, score and trajectory smoothness.

4 CONCLUSIONS

In this paper we presented the design, development and pilot evaluation of NeuRow, a novel BCI-VR system for MI training. In terms of classification performance, the NeuRow BCI training paradigm showed a high performance, scoring the first amongst other studies with similar feature extraction and classification methodologies. These data supports a positive effect of the combination of immersive VR and vibrotactile feedback to help users to produce vivid MI (resulting in more distinct activation of sensorimotor areas of the brain), which in turn that can lead to increased performance and learning (Sigrist et al., 2013). Furthermore, from the user experience point of view, we can see high mental effort as given by the TLX scales and low physical and temporal demands. Previous research in distinguishing difficulty levels with brain activity measurements indicated an average mental workload index of 26 (*SD = 12.9*) for the easy level, and 69 (*SD = 7.9*) for the hard level (Girouard et al., 2009). The combination of low physical demand (useful in low mobility patients), increased effort (a conscious exertion of power) and good classification performance (better control that can lean in goal achievement), constitutes a very promising finding for the incorporation of this technology in stroke rehabilitation, providing new possibilities for rehabilitation programs. Moreover, increased flow and immersion to the task, in combination with increased positive affect, are good elements for enjoyment of NeuRow that can be capitalized on to further motivate and engage users in their BCI training. From the correlation analysis between user experience -subjectively measured through questionnaires but also objectively measured through EEG activity- and in-game behaviour, we can see that people with increased workload will perform worse. Interestingly, we can see that users with fast response time in MI ability (as extracted from the mental chronometry assessment) performed better in the game, being it then an indicator of increased capability of MI. Having a fast and vivid sensation of kinesthetic imagery can be related to an increased modulation of sensorimotor rhythms (Neuper et al., 2005), resulting in better BCI calibration and hence higher in-game performance. In addition, the reverse correlation of the Engagement index with all the in-game variables shows an important connection between user engagement and in-game behaviour. This relationship can help in developing a neurofeedback closed loop were the engagement of the user is used to adjust parameters of the game. This would allow a dynamic adjustment of the game based on user performance and cognitive state. This could provide (1) a major assistance for new users and/or neurologically impaired people and (2) reduced levels of frustration and workload.

Overall, we showed that NeuRow, combining the use of immersive VR environment, sensory stimulation and motor-priming features, can provide a holistic approach towards MI driven BCIs. In this study we showcased user performance, user acceptance and important features for closing the loop in an implicit manner. Finally, NeuRow's features show promise and potential to be used for MI training in stroke motor rehabilitation. Future work will include a study with stroke patients with the ultimate goal to clinically validate NeuRow in a longitudinal MI-BCI study with functional brain imaging.

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