Non-immersive Versus Immersive Extended Reality for Motor Imagery Neurofeedback Within a Brain-Computer Interfaces

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Abstract. A sensory feedback was employed for the present work to remap brain signals into sensory information. In particular, sensorimotor rhythms associated with motor imagery were measured as a mean to interact with an extended reality (XR) environment. The aim for such a neurofeedback was to let the user become aware of his/her ability to imagine a movement. A brain-computer interface based on motor imagery was thus implemented by using a consumer-grade electroencephalograph and by taking into account wearable and portable feedback actuators. Visual and vibrotactile sensory feedback modalities were used simultaneously to provide an engaging multimodal feedback in XR. Both a non-immersive and an immersive version of the system were considered and compared. Preliminary validation was carried out with four healthy subjects participating in a total of four sessions on different days. Experiments were conducted according to a wide-spread synchronous paradigm in which an application provides the timing for the motor imagery tasks. Performance was compared in terms of classification accuracy. Overall, subjects preferred the immersive neurofeedback because it allowed higher concentration during experiments, but there was not enough evidence to prove its actual effectiveness and mean classification accuracy resulted about 65%. Meanwhile, classification accuracy resulted higher with the non-immersive neurofeedback, notably it reached about 75%. Future experiments could extend this comparison to more subjects and more sessions, due to the relevance of possible applications in rehabilitation. Moreover, the immersive XR implementation could be improved to provide a greater sense of embodiment.

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1 Introduction

In extended reality, or XR, experiences rely on creating an interactive environment and providing the perceptive consequences of these interactions. In accordance with the predictive coding theory [1], the human brain continuously generates and updates a mental model of the surrounding environment. This happens while receiving sensory stimuli, and, in turn, these models can predict imminent stimuli. In the real world, the movement of the body in space produces a continuous stream of both sensory stimuli and inner stimuli, but the XR community has currently focused on the only sensorimotor contingency as the prominent factor for presence. However, neuroscience has demonstrated that multi-perceptual integration of bodily signals, action, and embodiment are also critical to generate XR experiences [2]. Therefore, to develop novel XR-based applications, enhanced embodied XR experiences are relevant. For instance, this may apply to clinical scenarios, such as post-traumatic stress disorders, eating disorders, phantom limb pain, and autism, since these are related to a dysfunctional bodily self-consciousness. In such a scenario, mental training protocols are widely used.

With specific regards to neuromotor rehabilitation, conventional training protocols are used with the aim of recovering the functional damage or making an optimal use of residual motor assets. Some examples are the "Kabat" method [3], the "Bobath" method [4], and the "mirror therapy" [5]. In the "Kabat" method, the aim is to recover motor functionality through external proprioceptive stimuli by improving the altered movement. In the "Bobath" method, instead, functional recovery is attempted through proprioceptive learning and a tactile, visual and auditory sensory experience. Finally, mirror therapy represents a rehabilitation method that involves moving both injured limbs evenly and symmetrically in front of a mirror. The patient will have to observe the healthy limb, so that it will appear that the paretic limb is moving. This is a way to trick the brain into thinking that the movement is taking place normally and thus exploit the residual capacity of the injured limb by stimulating it with the optical effect of the mirror. Physical effort is also required from the patient in classical rehabilitation. On the contrary, these rehabilitation techniques have been recently combined with Brain-Computer Interfaces (BCI) based on motor imagery, i.e. a cognitive process during which the subject imagines a movement without performing it [6].

Nowadays, innovative systems try to exploit XR in such motor training. In particular, motor imagery is widely exploited in BCIs as a way for control and communication between the brain and an external device [7], and motor imagery-based BCIs are proposed in several fields because the brain activity generated by motor imagery affects the same brain areas involved during the execution of a movement [8]. However, although people have the ability to imagine, they do not get a sense of how they imagine. Therefore, a neurofeedback provided in XR can bridge this gap. Neurofeedback is a process by which the users are provided with feedback as a result of real-time processing of their brain signal. Moreover, neurofeedback reduces the training time required to be able to use the interface and increases the motivation and attention level of the users [9]. In neurorehabilitation, neurofeedback aids the patients in the self-regulation of their brain rhythms. It induces neural plasticity and promotes recovery of the injured motor nerve pathway [8]. The patients can receive multidimensional neurofeedback, i.e., visual feedback and haptic feedback simultaneously, in response to the executed motor imagery task. In this framework, XR technology can be exploited to create an immersive and realistic environment to provide users with sensory feedbacks [10].

Patient comfort is another priority. For this reason, BCIs are often based on electroencephalography (EEG) due to non-invasiveness, wearability, portability, and good temporal resolution [11]. To further enhance wearability and ease of use, the number of EEG channels should be minimized. Three channels is usually considered as a minimum number for motor imagery [12]. A wearable motor imagery-based BCI integrated with the XR aims to be a novel and emerging methodology for motor rehabilitation [13]. Indeed, letting the user become aware of his/her ability to imagine a movement can improve a rehabilitation protocol by engaging the patient during long and exhausting sessions.

In this contribution, both non-immersive and immersive neurofeedback in XR were explored as a means to remap motor imagery into sensory feedback. Notably, visual and vibrotactile sensory stimulation were proposed as a way to "feel" how they imagine movements. The final aim was to improve mental tasks, which are often unperceived and go beyond the five senses. The proposed systems aim to be wearable and portable and they could be suitable for neuromotor rehabilitation even outside a clinical setting. However, as a preliminary study, the systems were tested with healthy subjects. The paper is organized as follows: Sect. 2 presents the BCI system with XR neurofeedback and details both the non-immersive and the immersive version, Sect. 3 reports the results of preliminary tests carried out with these system versions, and Sect. 4 draws some conclusions as well as future steps for further research.

2 Materials and Methods

The present study focuses on wearable and portable BCI integrated with XR as a means to provide multimodal feedback related to motor imagery. This aims to allow the user to become aware of his/her ability to imagine a movement. As a consequence, it promotes the voluntary modulation of sensorimotor rhythms. The system prototypes were implemented with consumer-grade hardware and they are addressed to neuromotor rehabilitation, e.g. post-stroke. In particular, a limited number of differential channels were exploited during signal acquisition. A dedicated virtual environment was developed to provide either visual and haptic feedback to the user. These were modulated according to the ongoing brain activity related to motor imagery. Hence, brain signals were acquired and processed online in order to modulate the feedback in terms of direction and intensity. Two versions of the same system were proposed. In them, the differences were only related to the feedback actuators. In the first version, visual feedback was non-immersive because it was provided through a PC's monitor. Instead, haptic feedback was provided by a vibrotactile suit. In the second version, instead, visual feedback was ported to a virtual reality visor, while the haptic feedback was provided via the visor's controllers. Experiments were carried out according to a standard synchronous paradigm, as detailed hereafter.

2.1 System Implementation

Virtual Environment. The virtual environment for both versions was developed with the Unity Development Platform[1]. Regarding the visual feedback, the scene is represented in Fig. 1. In there, the visual feedback consisted of a virtual ball, which could horizontally roll to the left or to the right side of the scene. Its actual movement was modulated in terms of direction and speed in accordance with the measured brain activity. The edges for the ball movement were marked in the environment with two white lines on the two sides of the scene. Regarding the haptic feedback, the vibration was modulated in terms of direction and intensity according to the measured brain activity. For this modality, the feedback actuators are described below in distinguishing the non-immersive version from the immersive ones. Details about the feedback actuation are thus given along with such a discussion.

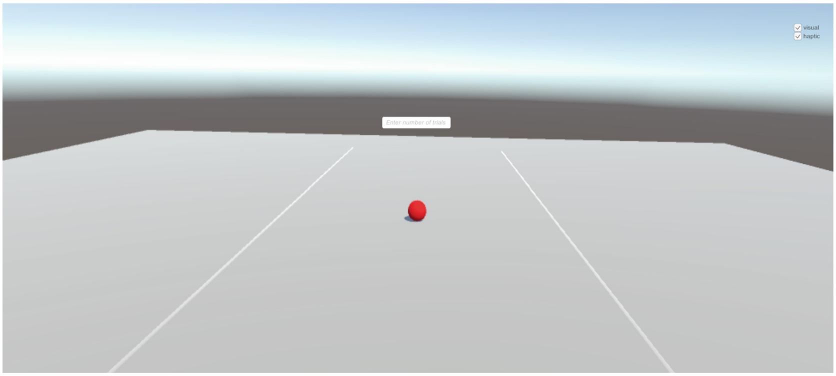


Fig. 1. Scene for the visual feedback within the virtual environment.

[1] https://unity.com/.

Non-immersive Version. Feedback actuators for the non-immersive version were first considered. The visual feedback consisted of a virtual rolling ball on a PC's monitor. This had an LCD 15.6" display (resolution 1920×1080 pixels) with a 60Hz refresh rate. Meanwhile the haptic feedback was provided by the vibrotactile suit from bHaptics Inc[2] (Fig. 2). This consists of a double 5×4 matrix with vibration motors on the front and back of the torso capable of actuating a chest vibrotactile stimulation. The vibration can be modulated in terms of duration, frequency and intensity. The suit communicates via Bluetooth and it was particularly controlled through the Unity application.

The SDK provided by bHaptics was exploited to modulate the suit haptic feedback. Vibration patterns were provided on the front of the torso starting from the center. They moved toward the left or toward the right according to the brain activity. The goal for the user was to maximally activate the haptic feedback on the back of the respective side.

Fig. 2. Wearable haptic suit with a double matrix of vibrating motors for vibrotactile feedback.

Immersive Version. The immersive feedback was provided through the HTC VIVE PRO EYE by HTC Corporation Inc[3]. This consists of a virtual reality headset with dual-OLED 3.5" diagonal displays (resolution 2880×1600 pixels), a 90Hz refresh rate, and a 110° field of view. The wireless controllers with SteamVR Tracking 2.0 sensors provide high definition haptic feedback and they should be held by hands (Fig. 3). In this version, the controllers were employed to provide vibrotactile feedback during the experiments, while participants did not actively interact with the environment through them. Like the suit, the vibration could be modulated in terms of duration, frequency and intensity.

[2] https://www.bhaptics.com/tactsuit/tactsuit-x40.
[3] https://www.vive.com/us/product/vive-pro-eye/overview/.

The SteamVR Unity Plugin[4] was exploited to provide an immersive interaction with the environment in the HTC system. The visual feedback was simply ported on the visor in this immersive version. Meanwhile, for the haptic feedback provided through the controllers, the vibration at the hand corresponding to the motor imagery task was modulated in terms of intensity. Notably, this intensity changed according to the measured brain signals.

Fig. 3. HTC VIVE PRO EYE virtual reality headset with hands-held controllers.

EEG Acquisition. EEG data were acquired by means of a FlexEEG headset by Neuro-CONCISE Ltd[5] with 3 differential channels over the motor cortex (Fig. 4). In this acquisition system, electrodes are located at FC3-CP3, FCZ-CPZ, and FC4-CP4 by following the standard 10–20 system for EEG recordings [14]. The ground electrode is placed at AFz. Despite the possibility to use dry electrodes, wet ones are generally preferred to ensure good signal-to-noise ratio and high signal reliability. Therefore, conductive gel was used in these experiments. Thanks to its wearable design, FlexEEG was properly embedded with the XR visor. EEG signals were sent to a custom Simulink model by using Bluetooth 2.0 wireless signal transmission and available Simulink APIs. Such a model involved online signal processing and responded to the application's timing.

2.2 Experimental Paradigm

The XR neurofeedback was implemented within a synchronous motor imagery-based BCI. The experiments consisted of two sessions per system version carried out on different days (four sessions in total). Each session involved three runs for calibrating the system and three runs for providing online neurofeedback. About 10min-break was given to the participant between these two phases. A single session lasted about 30min. Each experimental task consisted of imagining left or right hand movement depending on the indication and in accordance with an external timing. The motor imagery task to be imaged was randomized in

[4] http://steamvr.com.
[5] https://www.neuroconcise.co.uk/.

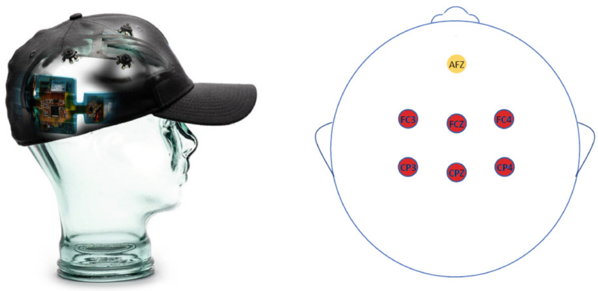
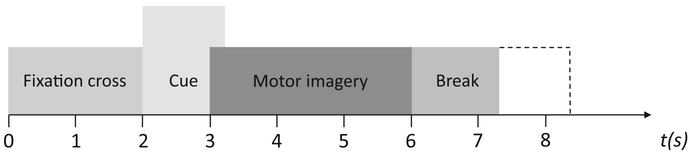


Fig. 4. Wearable and portable electroencephalograph with electrodes over the motor cortex.

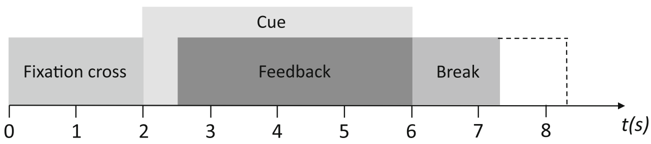
order to avoid any bias. A total of 30 trials per run were performed, so that 270 trials were carried out as a whole in both the non-immersive and immersive case. With reference to the standard paradigms of BCI competitions [15], Fig. 5 shows the timing diagrams of a single trial during the calibration phase and online feedback phase, respectively.

During the calibration phase (Fig. 5(a)), the participants performed the pure motor imagery. Each trial started with a relax period during which the participant had to stare at a fixation cross. Then, a cue indicated the trial to be carried out during the following "motor imagery period", lasting 3.00 s. Finally, a break with random duration concluded the trial. These indications always appeared on the PC's monitor. Hence, the calibration phase was non-immersive in both system versions. At the end of all the trials associated with this phase, the recorded EEG signals were exploited in order to train the algorithm for the online phase. In particular, the cross-validation technique was employed to find the 2.00 s time window within the 3.00 s of motor imagery in which the maximum overall classification accuracy and the minimum per-class accuracy difference were achieved. Thus, the algorithm was trained by considering this optimal window.

During the online feedback phase (Fig. 5(b)), EEG signals were classified during motor imagery execution in order to provide simultaneous feedback. After the fixation cross period and the cue, the signals were processed during each motor imagery window using a 2.00 s sliding window with a shift of 0.25 s until the end of the task. It is worth noting that, despite the previous case, the cue indication is here persistent during the whole motor imagery/feedback period. In terms of feedback, the goal for the user was to push the ball over the white line on the respective side of the virtual floor. At the same time, maximum vibration intensity was provided. In order to avoid user frustration and disengagement, the user received the feedback only when the class associated with the measured brain signal corresponds to the indicated task (biased feedback). If instead the assigned class did not match with the task, the ball did not move and the controllers did not vibrate. In any case, the intensity of the feedback was modulated according to the classification score.



(a) Calibration phase



(b) Online feedback phase

Fig. 5. Timing diagrams for a single experimental trial.

2.3 Signal Processing

The EEG signals were processed to modulate the neurofeedback during experiments, but also to assess the motor imagery capability of a subject after the experiments (offline analysis). In both cases, features were extracted from raw EEG data by means of the filter-bank common spatial pattern (FBCSP) algorithm [16] and then classified with a Naive Bayesian Parzen Window (NBPW) classifier. During online neurofeedback, the assigned class with its associated score were used in order to modulate the feedback direction and speed/intensity, respectively. The online operation of the system, including signal acquisition and processing, was implemented by means of a Simulink model communicating with the Unity application. Meanwhile, Matlab scripts were implemented to train the algorithm for online processing by relying on acquired EEG signals and to analyse these signals after the experiments.

In offline analyses, baseline removal was first applied by considering the 100 ms before the cue. Then, the FBCSP was used. In particular, (i) EEG data were digitally filtered using an array of bandpass filters from 4 Hz to 40 Hz, (ii) the common spatial patterns (CSP) algorithm was exploited for feature extraction, (iii) the mutual information-based best individual features (MIBIF) algorithm was used to select the most important features, and (iv) finally the NBPW was exploited to classify the features related to a specific task and to assign them the most probable class. Note that the CSP uses spatial filters to maximize the discriminability of two classes. Hence, binary classification was considered, but multi-class extensions would be possible as well. As a result of the NBPW, the most probable class and its probability were used to modulate the feedback in the online phase, as already mentioned above. The block diagram of the algorithm is recalled in Fig. 6.

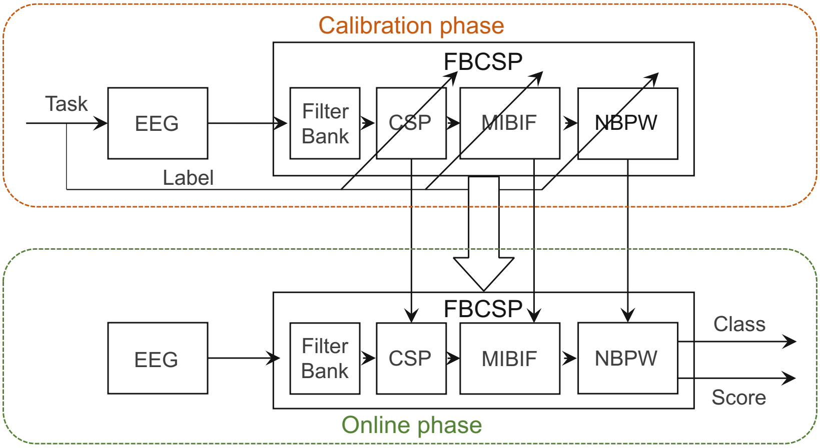


Fig. 6. FBCSP algorithm. EEG: electroencephalography, CSP: common spatial pattern, MIBIF: mutual information-based best individual features, NBPW: naive bayesian parzen window.

3 Results

3.1 Subjects

With the aim of evaluating the effectiveness of the proposed system, four right-handed healthy volunteers participated in the two experimental sessions per each system version (non-immersive and immersive). One subject was male and three were females (mean age 27). The subjects signed an informed consent before participating in the experiments. These were conducted at the Augmented Reality for Health Monitoring Laboratory (ARHeMLab, University of Naples Federico II) in Italy.

3.2 Classification Results

Data from each experimental phase were analysed as described before by applying a 5-folds cross validation with 10 repetitions. For both the calibration and the online phase, an optimal 2.00s-wide time window was selected per each subject. With particular reference to the results of the calibration phase, the criterion for an optimal choice of the time window was to maximize the classification accuracy while trying to also minimize the difference between accuracies per class. Therefore, the same criterion was adopted in also reporting the accuracy associated with the online feedback. These classification accuracies are reported in Table 1 and Table 2 for the non-immersive version and the immersive version, respectively. Each session and phase are considered separately.

It can be thus interesting to compare the two system versions. Referring to mean accuracies associated with the non-immersive case, it can be noted that the one associated with the calibration phases of both sessions resulted from 62%

to 64%. The effectiveness of the feedback is here evident and it consists of an accuracy improvement of about 10%. Notably, the non-immersive neurofeedback resulted more effective for the subjects S01 and S02.

Table 1. Classification results obtained with a 10-repeated 5-folds cross validation in the non-immersive neurofeedback case.

	Accuracy (%)			
	Session 1		Session 2	
	Calibration	Feedback	Calibration	Feedback
S01	57	84	67	75
S02	70	82	62	82
S03	63	68	65	64
S04	57	65	61	76
Mean	62	75	64	74

Instead, for the immersive case, it can be noted that mean accuracies remain between 61% and 66% for both the calibration and online feedback phases. Only in the Session 2, the improvement in mean accuracy is associated with neurofeedback, but due to a lowered accuracy in the calibration phase. Despite the previous case, subjects S01 and S02 are not improving with the immersive neurofeedback. Meanwhile, the improvements associated with S03 and S04 are compatible with the previous case.

3.3 Discussion

As a whole, the results reported above were not capable of proving the effectiveness of the immersive feedback while a substantial improvement was highlighted for the non-immersive case. Despite that, all subjects agreed that the immersive system was helping them to keep higher concentration throughout the experiment. A possible issue related to the immersive version of the system could be that participants were not familiar with using visor before the experiments. In addition, since the calibration phase was always delivered in a non-immersive modality, participants could have been confused when the modality changed during the session. Therefore, an immersive calibration phase could be explored in the future.

A more immersive visual feedback could be also explored. Indeed, the current one simply consisted of a simple porting to the visor of the non-immersive visual feedback, while an updated version could be realised. For instance, in motor imagery-assisted neurological rehabilitation, an embodied feedback could be implemented to perform mirror therapy. Finally, regarding data analysis, more insights could be done by going beyond classification accuracy. For instance, band

Table 2. Classification results obtained with a 10-repeated 5-folds cross validation in the immersive neurofeedback case.

	Accuracy (%)			
	Session 1		Session 2	
	Calibration	Feedback	Calibration	Feedback
S01	69	67	62	63
S02	74	60	63	63
S03	53	63	65	68
S04	63	68	56	69
Mean	65	65	61	66

power could be evaluated to understand if the neurofeedback enhances neurological phenomena associated with movement while keeping the mental workload low.

4 Conclusion

Extended reality has been recently considered in motor training and rehabilitation. Notably, motor imagery can be exploited in brain-computer interface systems integrated with extended reality as a novel way for communication and control of an external device. In doing that, people do not get a sense of their motor imagery capability and a neurofeedback could be exploited to that aim. Thanks to a real-time processing of brain signal, this aims to improve user engagement and hence performance, while reducing the training time.

The current study focused on the design, implementation, and preliminary testing of a wearable and portable brain-computer interface exploiting extended reality for neurofeedback associated with motor imagery. The system was implemented with consumer-grade hardware involving only three differential channels for EEG acquisition. The virtual environment was developed in Unity to provide visual and haptic feedbacks modulated according to the online processing of EEG signals. Both a non-immersive and an immersive system implementation were explored. The feedback was modulated in terms of direction and intensity by means of class and score, respectively. This processing relied on the filter bank common spatial pattern and a Bayesian classifier, which are widely employed in the field of brain-computer interfaces.

Preliminary experiments were carried out according to a standard paradigm for synchronous brain-computer interfaces by involving four subjects in two sessions per each system version. The classification results were thus compared to highlight the better neurofeedback modality. Overall, these preliminary results indicated a greater effectiveness of the non-immersive feedback in comparison with the immersive one, though the immersive environment favored concentration. The reason could be due to a lack of confidence with the visor usage.

Therefore, further experiments could explore an even more immersive virtual scene and a greater number of experimental sessions should be performed with a larger number of subjects as well.

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References

1. Kok, P., de Lange, F.P.: Predictive coding in sensory cortex. In: Forstmann, B.U., Wagenmakers, E.-J. (eds.) An Introduction to Model-Based Cognitive Neuroscience, pp. 221–244. Springer, New York (2015). https://doi.org/10.1007/978-1-4939-2236-9_11
2. Škola, F., Tinková, S., Liarokapis, F.: Progressive training for motor imagery brain-computer interfaces using gamification and virtual reality embodiment. Front. Human Neurosci. 329 (2019)
3. Kabat, H.: Studies of neuromuscular dysfunction; treatment of chronic multiple sclerosis with neostigmine and intensive muscle re-education. Permanent. Found. Med. Bullet. **5**(1), 1–14 (1947)
4. Kollen, B.J., et al.: The effectiveness of the bobath concept in stroke rehabilitation: what is the evidence? Stroke **40**(4), e89–e97 (2009)
5. Thieme, H., et al.: Mirror therapy for improving motor function after stroke. Cochrane Datab. Syst. Rev. **7** (2018)
6. Pfurtscheller, G., Neuper, C.: Motor imagery and direct brain-computer communication. Proc. IEEE **89**(7), 1123–1134 (2001)
7. Wolpaw, J.R., et al.: Brain-computer interface technology: a review of the first international meeting. IEEE Trans. Rehabilit. Eng. **8**(2), 164–173 (2000)
8. Wen, D., et al.: Combining brain-computer interface and virtual reality for rehabilitation in neurological diseases: a narrative review. Ann. Phys. Rehabilit. Med. **64**(1), 101404 (2021)
9. McCreadie, K.A., Coyle, D.H., Prasad, G.: Learning to modulate sensorimotor rhythms with stereo auditory feedback for a brain-computer interface. In: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 6711–6714. IEEE (2012)
10. Elbamby, M.S., Perfecto, C., Bennis, M., Doppler, K.: Toward low-latency and ultra-reliable virtual reality. IEEE Network **32**(2), 78–84 (2018)
11. Teplan, M., et al.: Fundamentals of EEG measurement. Measur. Sci. Rev. **2**(2), 1–11 (2002)
12. Leeb, R., Lee, F., Keinrath, C., Scherer, R., Bischof, H., Pfurtscheller, G.: Brain-computer communication: motivation, aim, and impact of exploring a virtual apartment. IEEE Trans. Neural Syst. Rehabilit. Eng. **15**(4), 473–482 (2007)
13. Cuomo, G., et al.: Motor imagery and gait control in Parkinson's disease: techniques and new perspectives in neurorehabilitation. Expert Rev. Neurotherap. (2022)

14. Klem, G.H., Lüders, H.O., Jasper, H., Elger, C., et al.: The ten-twenty electrode system of the international federation. Electroencephalogr. Clin. Neurophysiol. **52**(3), 3–6 (1999)
15. Brunner, C., Leeb, R., Müller-Putz, G., Schlögl, A., Pfurtscheller, G.: BCI competition 2008–Graz data set A. In: Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), vol. 16, pp. 1–6. Graz University of Technology (2008)
16. Ang, K.K., Chin, Z.Y., Wang, C., Guan, C., Zhang, H.: Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b. Front. Neurosci. **6**, 39 (2012)