Virtual reality embodiment in motor imagery brain-computer interface training

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Abstract

Purpose: This study investigates how the avatar embodiment in virtual reality (VR) influences training for operation of motor imagery brain-computer interfaces (MI-BCIs). In previous studies, we demonstrated the possibility to induce a BCI-based VR avatar embodiment (using mental commands instead of motion tracking) for purposes of training facilitation. This paper examines the relationship between BCI performance and subjective levels of embodiment, as well as differences in BCI performance achieved with training in two different VR environments. **Methods:** MI-BCI training variants with the following forms of feedback was studied: a) with feedback exploiting avatar embodiment in immersive VR (avatar movements indicating the user performance), b) with feedback exploiting avatar embodiment in gamified and progressively-paced VR training, and c) with symbolic feedback in the standard Graz protocol. On-line performance from the BCI experiments and questionnaires on the sense of ownership and sense of agency towards the virtual avatar were studied. **Results:** Questionnaire analysis showed that a robust sense of embodiment arose in the VR training environments, with a strong correlation between the reported ownership and agency towards the avatar. Interestingly, the achieved BCI performance was uncorrelated to both the ownership and the agency. Using gamification further increased the performance (but not the reported sense of ownership) in the training session. **Conclusion:** Embodiment in VR mediated by synchrony between mental commands and visual stimulation in VR arises under different conditions than embodiment based on visuo-motor synchrony. Consistency between the perceived sense of ownership and agency plays a more important role than the ability to issue MI-BCI commands correctly. These findings help to elucidate the positive effect of embodiment to initial steps in BCI training and can be leveraged in future MI-BCI training designs.

Keywords: brain-computer interfaces, gamification, motor imagery, sense of agency, virtual embodiment, virtual reality

1 Introduction

This paper examines intersection of two important concepts in the field of human-computer interaction; brain-computer interfaces (BCIs) and virtual reality (VR). Both were conceived more than a half century ago, but started to gain the potential for consumer adoption rather recently. Especially the BCIs, while having been subject of intense research during the last decades, suffer from flaws that prevent most practical applications. VR seems to be a promising tool aiding to bring the BCIs towards users.

VR systems use the body for interaction. Ideally, any part of the body can take part in the interaction with an advanced VR system. VR aims to leverage the most of the sensorimotor loop [1] – the motor system as the human "output interface" which is coupled with the sensory system serving for information retrieval. VR intervenes in the midst of the sensorimotor loop, using the data associated to the motor system (position and orientation of the body parts) as inputs, providing in turn synthesized percepts with correct transformations to the sensory organs. VR can be seen as a sensory illusion controlled by bodily movements. This illusion can easily incorporate a visual rendering of a selected body (virtual avatar), acting in synchrony with the user movements.

BCIs aim to allow humans to communicate and act while bypassing the motor system [2]. One of their main purposes is to enable communication in people who can not move at all, which is accomplished by using mental commands (translated from the brain signals) as the input for computers, robots, and other machines. Healthy users can leverage BCIs for monitoring of affective and cognitive states [3], e.g. for using information about estimated level of attention as additional input for computer games or meditation training [4].

To use a BCI for the purpose of voluntary communication, users must first go through a training process or at least a calibration of the system. This research is focused on the BCI communication paradigm based on motor imagery (MI), which exploits changes in scalp-recorded neural activity created by focused imagery of bodily movements. Motor imagery brain-computer interface (MI-BCI) is a system for voluntary control of devices, which makes use of several (typically one to four) classes of mental commands, mediated by imagined movements of different body parts.

This paper presents results on MI-BCI training facilitation with VR avatar embodiment [5] (an effect allowing body ownership transfer illusion). The hypothesis was that combination of BCIs and VR would lead to reduced training times by providing rich and natural feedback; i.e., feedback that is in congruence to the training task. Progress in the training task for BCI communication (imagery of hand movements) was indicated with the adequate feedback of hand movements performed by the surrogate body in VR.

Data from 3 groups of participants taken from 2 previous experiments [6, 7] (part of a bigger study on embodied VR MI-BCI training [8]) demonstrating the benefits of embodiment in MI-BCI training were studied to elucidate the mechanism behind this effect. One studied group of participants was trained using the standard training method with feedback using symbols. Training of the second group was performed with avatar using virtual embodiment (using signals corresponding to the imagined movements as inputs for the VR, and the movements of the "surrogate" avatar body as the output). Finally, the third group was trained with a gamified VR application with avatar embodiment. A simple game was wrapped around the training procedure and participants were trained using a more visually appealing and engaging environment. Moreover, training of the latter group of participants incorporated progressive increase of the training pace.

This paper presents comparison of the between-group results, as well as overall analysis of the data on embodiment and BCI performance. The discussion is focused on the grounds of the facilitating effect of VR embodiment to the BCI communication training.

2 Background

Electroencephalography (EEG) is a brain imaging method based on scalp recording of weak electrical currents corresponding to the cortical activity [9]. The EEG electrodes are placed on the scalp and simultaneously record a multichannel EEG signal. Each channel represents voltage fluctuations in time as the difference between the scalp electrode and a reference electrode (not placed on the scalp). EEG signal is created from post-synaptic discharges of large groups of neurons (i.e., electrical changes in membrane potential of the receiving neural cell after the synaptical transmission), and the resulting signal is called neural oscillations. Neurons contributing to the EEG activity must have a similar orientation and fire in synchrony [10]. The signal recorded by an EEG electrode originates from hundreds of millions neurons in the cortex [11]. To estimate sources of EEG signals, a high number of electrodes is required [12].

Due to its portability, low price, acceptable spatial resolution, and exceptional temporal resolution (allowing the data retrieval process in millisecond steps) [13], EEG is the most common choice for implementation of the BCI systems [14]. Downsides of the EEG usage include the necessity to apply a conductive gel (paste or a solution is sometimes used) to the electrodes, as the "wet electrodes" still outperform the "dry electrodes" in signal quality. However, novel types of dry electrodes show recording qualities comparable to the gel-based electrodes [15]. Usage of the gel introduces practical issues to the BCI usage: longer set-up times, corrosion of the electrodes, drying out. Moreover, the application of the conductive gel causes notable discomfort to the users.

MI-BCIs systems typically make use of EEG to gather the brain signals. Covert rehearsal of bodily movements produces distinct changes in the sensorimotor rhythm. Specifically, decrease of the amplitudes of central mu and beta rhythms is the common correlate of the MI [16], caused by disruption of the synchronized resting-state neuronal firing during motor inactivity [17]. This evoked change in ongoing neural activity was coined the event-related desynchronization (ERD) [18]. ERD commonly occurs during the programming, preparing, and executing motor actions. MI-BCIs exploit the fact that a similar desynchronization is triggered by mere imagery of the movement execution [19]. ERD following the process of MI typically originates at the locations in the motor cortex responsible for sending motor commands to the corresponding body part, thus near the central sulcus in the brain [20]. To quantify the ERD, the EEG time-signal is transformed to the frequency domain, and the percentage change in mu and/or beta band power is calculated using Formula 1 [21] (BP stands for band power, pre and post refer to the event in ERD/ERS):

$$ERD\ [\%] = 100 * \frac{BP_{post} - BP_{pre}}{BP_{pre}} \tag{1}$$

From the user perspective, control strategy in MI-BCIs consists of focused imagery on movement of own hands, feet, etc [14]. Sending commands with an MI-BCI is conditioned by the accurate classification of mental states. Although most people have some sensorimotor rhythm modulation ability [22], training is needed to achieve the level where classification algorithms are able to distinguish between the desired MI commands.

The training is usually performed by repeatedly asking the user to perform the MI of specified body parts. Immediate visual feedback from the system follows, important for allowing to understand if the MI command was or was not recognized successfully (see Figure 1). One of the goals of the training is to enhance the ability to produce ERDs in motor cortex areas [23], in turn allowing better prediction capabilities by the machine learning side of the BCI system [14]. The training process is a co-adaptation; while the user is guided with the help of neurofeedback, the classifier in the BCI is trained as well [14].

Training for MI-BCIs is a mentally demanding process. Users must direct their focused attention to the movements of hands or feet for prolonged amounts of time, while no actual movement is permitted during the sessions. Moreover, the commonly used training protocol uses symbolic visual instructions and abstract feedback forms to communicate successfulness of the ongoing training MI commands. This symbolic visual feedback interferes with the ongoing MI trials of the participant, leading to attention split between comprehension of the feedback and focusing on the imagined body movements [24].

Numerous works highlighted the importance of the human-facing side of the BCI [25–29]. Main criticism towards standard training protocols considered ignoring elementary psychological findings about the optimal forms of training (e.g., using progressive or adaptive task design, exploiting rich feedback modalities [27]). Some of these problems can be alleviated by exploiting gamification, which can be defined as "the use of game design elements in non-game contexts" [30]. In the BCI context, gamification is helpful especially as it aims to improve immersion and motivation [31].

VR offers an unprecedented capability to replace the visual aspect of having a body with a designed avatar "body". This allows for investigations into the nature of the body ownership, as well as for various utilizations of this newly assigned virtual agent [32–35]. Feasibility of the full-body ownership illusion, the cornerstone of the experience of being inside a virtual body (virtual embodiment) [5], was demonstrated by Petkova and Ehrsson (2008) [36] using a set-up based on head-mounted display (HMD). They developed a body swap illusion using a real-time video feed showing the first-person view on a manikin or other person, played in the HMD of the participant. This effect was later transferred into the immersive VR by Slater et al. (2009) [37].

Human brain mechanisms for recognition and self-attribution of the "attached" body use prior knowledge and available sensory data [38]. In VR, virtual embodiment arises thanks to the fact that the visual contact with own body is removed and the avatar takes its place. First person view of a body that acts in accordance with one's will creates a strong embodiment illusion, including the self-attribution of the avatar body. Consequently, people immersed in VR with an embodied avatar tend to keep their avatars away from virtual dangers, eliciting similar physiological responses to the threats as if they were performed in the physical reality and the real body was at stake [39].

When the body is self-attributed, one experiences what is termed the sense of (bodily) ownership (SoO) [40]. The sense of being the author (agent) of the voluntary actions is termed the sense of agency (SoA). Both of these senses are hold towards the virtual avatar body. Even though agency can be defined in terms of the voluntary movements [41], covert actions (such as creating an intent or a thought in the stream of thoughts) can and should be also included in the BCI context [40, 42]. BCIs exclusively allow manifestation of one's SoA using covert actions; i.e., BCIs allow for translation from the intention to an action without any movement.

Feasibility of using embodiment for MI-BCI training was proved by Perez-Marcos, Slater, and Sanchez-Vives (2009) [43], who created a VR environment allowing participants to feel the SoO towards a virtual hand controlled by the MI actions. Consequently, the SoA towards its movements arose. Firstly, the participants were trained for the MI-BCI operation using left hand and right foot imagined movements (to a level of accuracy of at least 70%). Then participants watched opening and closing movements of the hand (delivered using a VR system based on 3D stereoscopic projections) using the learned MI-BCI actions. It should be noted that the movements of the hand were not fully aligned with the MI task (left hand and right foot MI were represented as the left hand movements).

BCI-induced full-body embodiment was primarily investigated with the robots first, as it can facilitate the telepresence (presence at a different physical place). Proof-of-concept of the control of a humanoid robot carrying out complex tasks (fetching objects using BCI commands) was performed by Bell et al. (2008) [44]. In experiments by Alimardani et al. in 2013 [45] and in 2016 [46], participants reported a high SoO towards the hands of a humanoid robot controlled by MI-BCI. Significant learning difference between embodied MI-BCI control using human-like hands and a pair of metallic grippers was not found in span of one session; however, the group trained for MI skills using the humanoid hands performed better in a follow-up session, suggesting a positive role of human-like embodiment for the BCI control [47]. They also investigated difference between an MI-BCI- and motion-tracking-based control of the robot. Surprisingly, higher level of the SoO toward the robot was found in the MI-BCI condition in comparison to motion tracking control [47]. Even introducing a delay to the control mechanism did not break the SoO illusion when BCI was used to control the system. This was not true for the SoA, as the SoA towards the non-body seem to follow the same rules as for the bodily actions – it is weakened with discrepancies between the action and its outcome [48].

Most of the studies on body ownership in context of the MI-BCIs utilized Graz protocol for the training, and after sufficient level of accuracy was achieved, the actual embodied control phase took place. Vourvopoulos et al. (2016) [49] used an embodied form of multisensory feedback in their Neurow game, a Graz-based MI-BCI training implementation. The game had a form of a rowing simulator, and beside the visual feedback, participants received a vibrotactile feedback to each hand. Self-paced rowing driven by the hand MI followed the initial training, to further strengthen the MI skills in participants. However, the self-paced MI task was not used for classifier training. Braun et al. (2016) [50] used a pair of anthropomorphic robotic hands to convey MI feedback even for the training stage. It was also demonstrated that the strong sense of embodiment arising in VR aids the BCI-mediated neurorehabilitation [51–53].

3 Methods

This paper summarizes data from two previous experiments and presents extra cross-dataset analyses between the groups in original publications. The analyses were focused on the embodiment in the context of MI-BCIs and the relationship between BCI performance and embodiment.

Embodiment was quantified using questionnaires on the SoO and the SoA (standard questions from studies on body ownership were used, based on [54, 55]), answered on a Likert scale from -3 to +3 (one questionnaire after the BCI session).

Equipment used to present the VR scenes comprised of Oculus Rift HMD (Facebook Technologies, LLC, USA) with resolution of 1080x1200 per eye, 90 Hz refresh rate, 110 field of view, and rotational and positional tracking. EEG signals were recorded using light-weight wireless device Enobio 32 (Neuroelectrics, Spain).

BCI performance was calculated as a) percentage of the total time spent in the correct MI state (when recognized by the classifier) and b) percentage of the successfully recognized MI actions (per-trial). Normalization between the first study [6] in Section 3.1 and the second study [7] in Section 3.2 had to be performed, the details on normalization are provided in Section 4.1. Additionally, bit-transfer rate (BTR) was calculated and used in the comparison. BTR describe the amount of information transferred by the BCI and contrary to accuracy, it reflects the increasing pace of the training runs. Formula from [56] was used, adapted to take into account the trial length as used in [57] (Formula 2). For the purposes of comparing the first run of training (when the feature set for the initial training of the classifier was being created), cross-validation classification accuracy (CCA) was analyzed.

$$BTR = \left[log_2 N + P * log_2 P + (1-P) * log_2 \frac{1-P}{N-1} \right] \frac{60}{trial\ length} \tag{2}$$

Additionally, differences in EEG spectra were computed for purposes of establishing possible correlates of embodiment in MI-BCI control. The entire set of EEG channels was utilized for cleaning of the data using ICA. EEG channels that were analyzed for the SoO correlates were located in the sensorimotor cortex (centroparietal channels CP1, CP2, CP5, CP6, and Cz). To evaluate the effect of embodiment on the spectral properties of the EEG signal, differences between the participant's brain signals from the late and the early phase in recording of each medium were calculated. In particular, first 30s of each recording were taken as the *baseline*, and last 30s of the recording represented the *active* part. The differences were than calculated in the same fashion as computation of the ERD in MI experiments (see Formula 1).

3.1 Study comparing standard and embodiment-based training

The first study of training for MI-BCI leveraging the VR with avatar embodiment [6] aimed to assess the difference between usage of the standard Graz MI-BCI training protocol with symbolic feedback (see Figure 1) and the newly designed embodied paradigm for BCI training (Figure 2). For purposes of creating the embodied training, a body ownership illusion with binding of the SoO and the SoA using actions performed with the MI-BCI had to be implemented. That was achieved by initiating the experiment directly with the synchrony between mental effort and visual outcomes of the VR environment, to facilitate

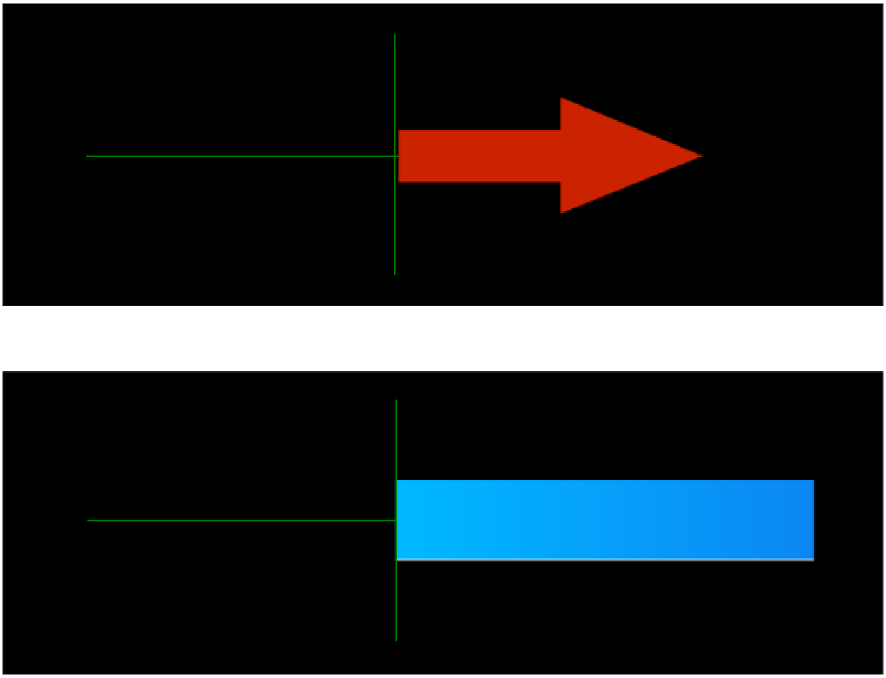

Fig. 1 Implementation of the Graz training protocol (symbolic guidance); top: instruction to perform a right hand MI trial, bottom: feedback (an extending bar) representing a relatively confident classifier decision that the current participant's mental effort belongs to the right hand MI class.

the body ownership transfer (embodiment) from the beginning of the experiment. In other words, active thought process focused on the imagery hand movements bound to the visual representation of the moving virtual hands was the driving mechanism behind the BCI-mediated embodiment.

Design of the VR scenes for interaction with MI-BCIs is subject to constraints, arising from the necessity to maintain a stable bodily posture without engagement of voluntary muscles, including minimization of the eye movements. The reasons for that are that the ongoing EEG recording is prone to artifacts generated either by bodily or by external sources. Bodily artifacts are mainly caused by muscle activity from the facial area and the muscles around the neck. But even movement of the other parts of the body would have unwanted effects on the signal, either by generation of the EEG artifacts, or by contamination of the recorded signals by neuronal activity originating in the motor actions.

In the very first run of the training, the EEG data for personalized per-trial neurofeedback were not available. For that reason, movements of the avatar were carried out without an input from the BCI (the avatar performed the hand movements with natural speed). Still, participants were required to synchronize their mental imagery to the observed movements, to a) provide an

Fig. 2 Screenshot from the VR scene used for the training in the *Embodied* group of participants (resting phase).

initial feature set for the classifier training (system training with the features containing MI patterns); and b) facilitate the embodiment illusion due to the synchrony between the users' MI effort and the visual feedback. Motor action observation is known to contribute to ERD strengthening during the MI [58], further facilitating the initial training step.

The proposed embodied training aimed to correct sub-optimal elements of the training procedure, especially the feedback modality (incomprehensible guidance that is causing split of attention between the task and the provided feedback), touching the motivational aspects of the training. Feedback on each MI training trial was bound to the movements of the avatar, specifically its speed; natural movements indicated good BCI performance, while movements that were slowed-down (eventually almost to the point of fully stopping) indicated problems of the BCI system to comprehend the user EEG inputs (i.e., poor performance).

From the 30 participants in this study, control group (N = 15) was trained using the Graz training protocol (implemented in Openvibe [59]) on the standard computer screen, while experimental group (N = 15) was trained using the novel protocol with avatar embodiment. BCI control was mediated using imagined movement of left and right hand, aiming to push the virtual button in front of the participants. After two runs of the training, all participants accomplished the same task – pushing of the virtual button. Brain signals were collected using a 20-sensor set-up based on a lightweight wireless EEG device.

Questionnaire results on embodiment revealed the mean SoO was equal to 0.700 (SD = 1.670) and the mean SoA rating was 1.400 (SD = 1.283). These values show a relatively high sense of embodiment for the novel design. See the original paper [6] for a detailed information on the study.

3.2 Study using gamification and progressive pace for training

Design of the follow-up VR application was based on a gamified variant of the MI-BCI training [7]. The standard trial-based form of the MI-BCI training was preserved (randomized training trials grouped into several stages, with given cue before each trial, and randomized rest period after each trial). The gamified training environment employed themed environment and score points, while the challenge arose mainly from the progressive increase of the speed across several training runs (levels). Feedback on user progress was provided using three modalities:

1. Feedback embodied into the avatar body using varying speed of avatar hand movements (real-time)
2. Vibrotactile feedback to the corresponding hand mediated by the VR controllers (real-time)
3. Score displayed in the VR scene (post-trial quantification of the trial accuracy)

The environment depicted in the VR scene was set in the outer space, participants were virtually transferred inside a cockpit of a spaceship with an Earth-like planet ahead (see Figure 3). The gamified training objectives consisted of shooting flying asteroids depending on their position (using left hand MI if the asteroid flew from the left side of the spaceship, right hand MI if from the right side). The spaceship contained a simple control panel consisting of a low number of interaction elements that triggered the weapons shooting the asteroids flying towards the planet. At rest, avatar hands in VR rested on the tilted spaceship control panel, while hands of the participant were positioned in a pair of Oculus Touch VR controllers (see Figure 4).

Training was designed as progressive; i.e., pace of each run was higher than the preceding one. The user evaluation consisted of six runs of the training,

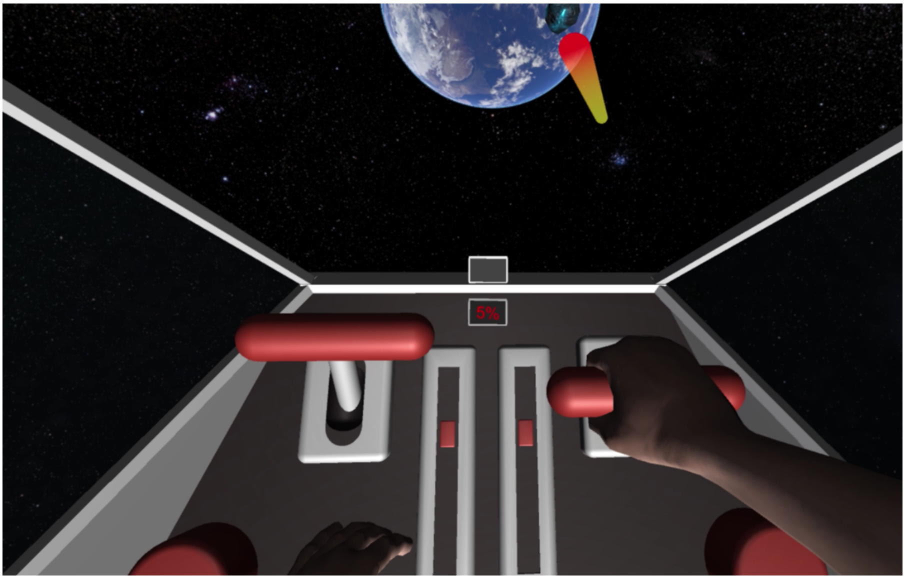

Fig. 3 VR feedback representing a recently finished right hand MI trial in the *Progressive* group.

while the first run consisted of MI facilitated by motor observation and the other runs provided participant with increasingly faster paced training. Last run inquired into a modality change experiment (post-trial discrete feedback only, without the real-time feedback). For more details please see the paper [7].

The VR training environment was evaluated in a between-subject user study with 19 participants (N = 20 including a participant falling below the chance level) performing 6 runs of the training. Signals were collected with 28 sensors using the same device as in the previous study. Questionnaires revealed a surprisingly high positive affect after the experimental session (mean 6.763, SD = 0.348, on a scale from 1 to 7). No participant reported the engagement or interest lower than 6 out of 7 points. Mean of the SoO statements was 0.768 (SD = 1.190) and the mean SoA was 1.290 (SD = 0.947).

3.3 Compared groups and results

The following 3 groups are analyzed in this paper:

- From the user study comparing the VR training with avatar embodiment to the standard method [6]
  - *Control* group (participants trained with the standard protocol)
  - *Embodied* group (participants trained with embodied avatar in VR)
- From the user study on gamified progressive training in embodied VR [7]
  - *Progressive/Gamified* group (participants trained with embodied avatar in gamified, progressive VR)

Fig. 4 Positioning of the hands during the experiment in [7].

To perform the analysis covering all these datasets, the following was taken into account:

- Accuracy and BTR in the 3rd run (maximal number of common training runs for all datasets)
- Accuracy and BTR of the best run per participant
- Number of participants not surpassing the chance level
- CCA in the first run without real-time feedback (to study the influence of the initial VR embodiment with motor action observation)

Non-parametric statistical tests were used due to non-normal distribution of the data.

4 Results

4.1 Normalization of the performance results

4.1.1 Accuracy metric used in the analyses

In [6], the on-line accuracy was reported as an average of percentages of time in each trial spent in the correct MI state. Another metric of on-line accuracy based on number of hits (percentage of number of trials with >50% successful time) was used in [7], representing the percentage of successfully issued commands using a two-class BCI. In comparison to the accuracy metric from [6], it also shows a stronger correlation to the CCA. In *Control* group r = 0.746, p = 0.543 versus r = 0.523, p = 0.229; in *Embodied* group r = 0.619, p = 0.024 versus r = 0.480, p = 0.097; in *Progressive* group r = 0.714, p = 0.001 versus r = 0.620, p = 0.005 (Spearman tests). Consequently, the metric based on

Group	N	Accuracy (run 3)	Accuracy (best run)
Control	7	62.286% (8.655)	62.286% (8.655)
Embodied	13	65.385% (16.132)	67.153% (14.960)
Progressive	19	67.105% (10.603)	75.842% (11.251)
Control (all)	15	53.067 % (11.386)	53.067% (11.386)
Embodied (all)	15	63.333% (15.886)	64.867% (15.109)
Progressive (all)	20	66.250% (11.007)	74.400% (12.709)

Group	N	BTR (run 3)	BTR (best run)
Control	7	0.267 (0.396)	0.267 (0.396)
Embodied	13	0.700 (1.306)	0.728 (1.292)
Progressive	19	0.825 (0.949)	1.992 (1.992)
Control (all)	15	0.160 (0.288)	0.160 (0.288)
Embodied (all)	15	0.606 (1.234)	0.631 (1.223)
Progressive (all)	20	0.784 (0.942)	1.893 (1.606)

Table 1 Comparison of the BCI performance across all tested groups; average on-line accuracy and BTR. SD is in parentheses. Groups marked as *all* include sub-chance-level participants.

Run #	Avg. trial length	Max. MI length
2nd	12.853	8.8
3rd	8.977	5.15
4th	7.143	3.93
5th	6.098	3.325
6th	7.158	3.9

Table 2 Averaged duration of a trial including the rest period in each of the runs (levels) in the *Progressive* group (Avg. trial length) and a maximal duration of the MI part (user effort) of a trial (Max. MI length).

number of hits was utilized for the overall analysis, and all the performance results from [6] were recalculated for purposes of this paper.

4.1.2 Differences between the accuracy metrics and the BTR

In [6], the average trial length was 14.805 s (feedback training) and 14.628 s (evaluation run), including the rest periods. The trials were significantly shortened in the follow-up study (min = 6.098 s, max = 12.853 s), see Table 2. Consequently, the former BTR values are very low, and the on-line accuracy serves better for comparison of the performance in the three conditions. In particular, accuracy in the 3rd run can be used to compare the performance after the same amount of training trials (from the two preceding training runs, with one including feedback).

Nonetheless, the average of the total training duration was 24.616 minutes in the comparison study and 28.153 minutes in the gamified progressive study. The best run accuracy represents the performance after a comparable time spent training (rather than after the same number of training trials performed). But still, the length of the training in the latter study was increased by 14.369%.

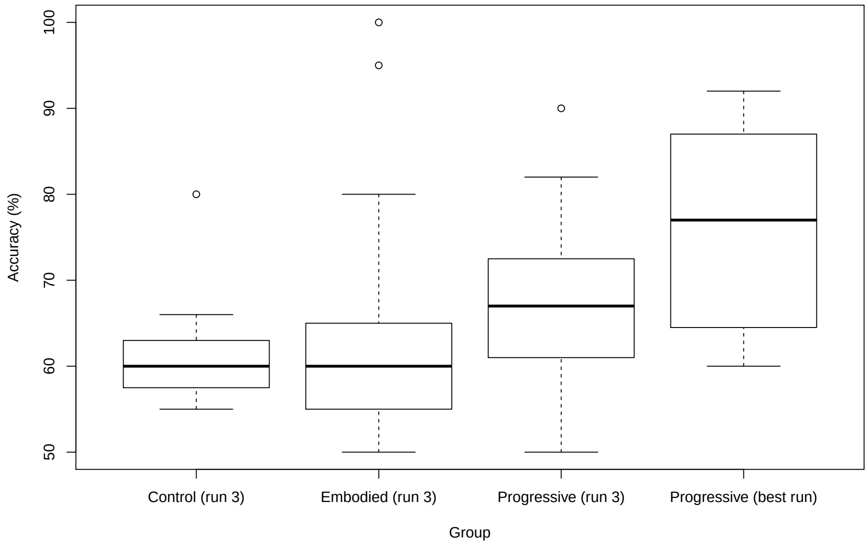

Fig. 5 Boxplots showing per-group BCI performance (accuracy).

The BTR values demonstrate the performance increase obtained by employment of the higher pace and the progressive design of the *Progressive* group, compared to the initial embodied design of the *Embodied* group.

4.2 BCI performance comparison

4.2.1 Accuracy and BTR per training method

Table 1 contains average performance results per-group (accuracy and BTR), while Figure 5 shows boxplots representing the average accuracy. The method used in the *Progressive* group produced the best results in all performance metrics. The analyses were focused on the subsets of participants who were able to surpass the chance levels, but results including the sub-chance-level participants (N = 11, details in Table 3) are stated as well.

Performance variability among BCI users accounted for a low statistical significance of the differences among the groups. Generally, the differences are worth testing for statistical significance if the sub-chance-level participants are included in the sample. Sample sizes of groups after pruning of the subjects without any control become low and strongly unbalanced. The strongest difference (tested with Wilcoxon test) is between accuracy values of *Progressive* and *Control* group with $W = 51.500$ and $p = 0.001$ (with the sub-chance level participants included).

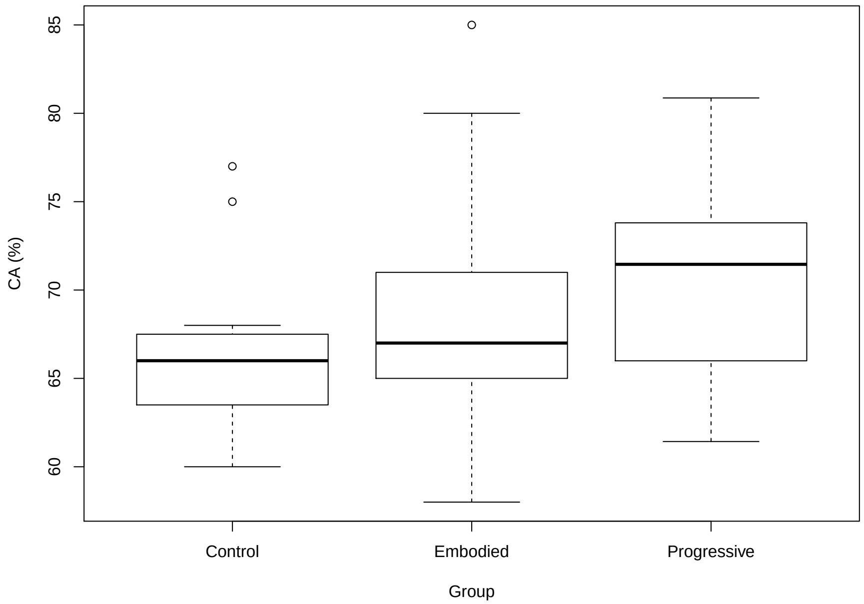

Fig. 6 Boxplots showing CCA of the dataset corresponding to the initial training. The results are shown per training method, without the sub-chance-level participants.

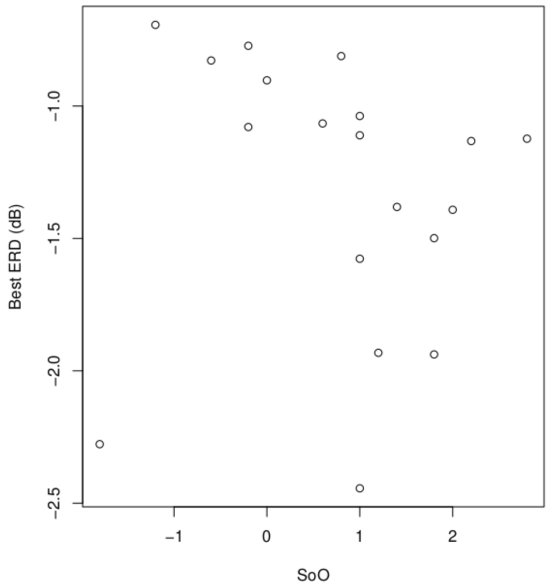

Fig. 7 Relationship between the SoO and the ERD in [7] (*Embodied* group). Apart from an outlying participant, the higher SoO was bound to the stronger ERD.

Group	N	N [s-ch-l]	Rate
Control	15	8	56.333%
Embodied	15	2	13.333%
Progressive	20	1	5.000%

Table 3 Number of participants (*s-ch-l* stands for sub-chance-level) not surpassing chance level (third column) in any of the runs per MI-BCI group.

4.2.2 Participants below the chance level

Performance was analyzed from the subset of participants surpassing the 50% chance level in at least one of the runs. Nevertheless, participants below that line are also important to take into account, as they can be considered an indicator of the BCI illiteracy (ratio of untrainable participants). Table 3 contains an overview of the percentage of participants not able to surpass the chance level in any of the runs in a session.

Even though the comparison was carried out among groups with different number of runs (the *Progressive* group with 5 on-line runs and the other two groups with 2 on-line runs), all but the one participant in the *Progressive* achieved >50% accuracy already in the first two runs. Thus even after comparison of the data from the first two runs only, the figures remain the same. This might be caused by simply more engaging design of the *Progressive* training compared to the *Embodied* training, but the number of sub-chance-level individuals is not very different in these two groups. Nevertheless, comparison to the *Control* group indicated both embodied designs as a significant improvement.

4.3 Embodiment and BCI performance

4.3.1 Effect of the initial embodiment

Effect of the combined MI and motor observation during the first stage of the training was assessed using the CCA in the first run (see Figure 6). This CCA represents the initial ability of the classifier to distinguish between the classes based only on the feedback-less training (VR avatar movements were shown, but with no input from the BCI), thus allowing to estimate how much the embodiment facilitated the differences between participants' ERDs for the left and right hand MI.

Results show that the *Control* group had a lower CCA (mean 66.267%, SD = 4.621) than the other groups (*Embodied* mean 68.600%, SD = 7.089; *Progressive* mean 70.821%, SD = 5.268). The difference is statistically significant between the *Progressive* and the *Control* groups (W = 222, p = 0.017), suggesting that the first stage of training with embodiment illusion indeed helped the initial classifier training, compared to the training with the standard Graz protocol.

Future work should investigate the effect of movement observation (in comparison to the intentional MI) on the initial ERDs. Removal of the real-time feedback in the progressive MI-BCI training study provides evidence that the

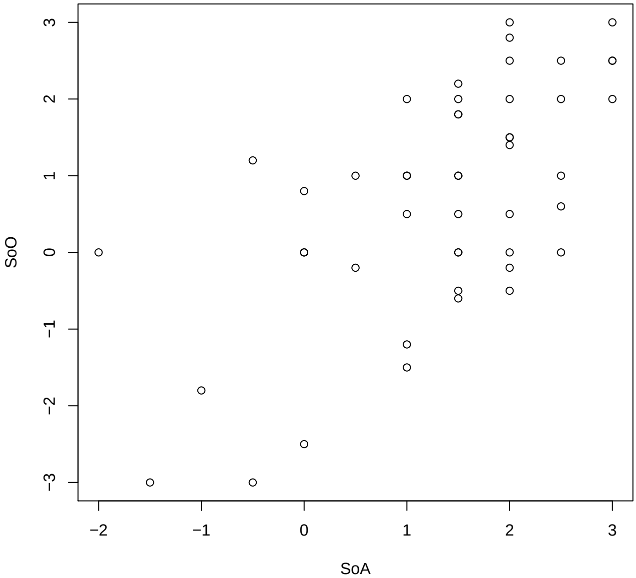

Fig. 8 Scatterplot showing the relationship between the reported SoO and the reported SoA (Spearman r = 0.581, p = 0.000, N = 49). Participants tended to experience a high ownership towards the virtual hands controlled by the MI-BCI when the notion of control was also high, indicating sense of embodiment towards the virtual avatar.

training is not completely hindered after the movement observation is removed from the feedback, but more data on the relationship between MI, motor observation, and ERD generation should be gathered.

4.3.2 SoO, SoA, and BCI performance

First of all, *Progressive* group had the SoO correlated to the magnitude of the ERD. High correlation coefficient and significance were reached in this group (r = -0.698, p = 0.001, N = 18; see Figure 7). But in the other two groups, the ERD–SoO relationship was not confirmed.

Very strong correlation (r = 0.581, p = 0.000, N = 49) was present also between the reported SoO and the reported SoA (see Figure 8). Interestingly, the SoA and the BCI performance were not correlated (r = 0.064, p = 0.660, N = 49), see details on Figure 9.

Finally, correlation between the SoO and the on-line performance was not found (the correlation coefficient was with r = 0.018, p = 0.901, N = 49; see Figure 10).

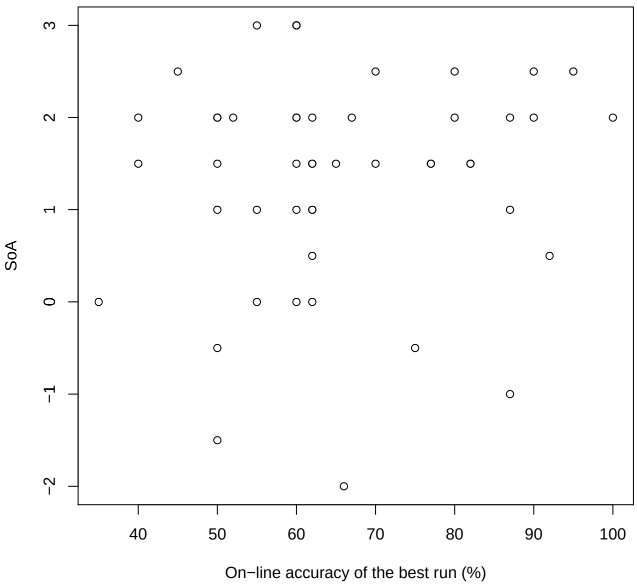

Fig. 9 Relationship between the SoA and the actual control proficiency (on-line accuracy of the best run). As the hand movements of the avatar correlated to the participant intentions in case of a good BCI performance (and participants were aware of this fact), correlation between the BCI performance and the SoA (as the self-report on the perceived performance) was expected. However, this was not confirmed.

4.3.3 Comparison of the SoO between the BCI experiments

The results for the SoO were comparable in the two environments creating embodiment based on MI-BCI control. Specifically, mean = 0.700 (SD = 1.670) in the first study on embodied MI-BCI training and mean = 0.768 (SD = 1.190) in the progressive design of the training (Wilcoxon rank sum test showed no statically significant difference with W = 274 and p = 0.829). It is interesting to relate the perceived SoO to the congruency between the body position of participants and the body position of the avatar in the VR scene (see Figure **??** for comparison of the avatar body position in both experiments).

The first experiment included a greater posture congruency (participant's hands laid on the table, congruently to the visual representation in the VR), which could consequently contribute to a greater proprioceptive mismatch when the avatar moved the hands. Position of the hands in the second experiment included a positional mismatch (resting in the Oculus Touch controllers in reality, but were positioned on the tilted spaceship control panel in the VR). Participants did not mention problems with proprioceptive mismatch in the qualitative reports in the second experiment (as did some of the participants in the first experiment).

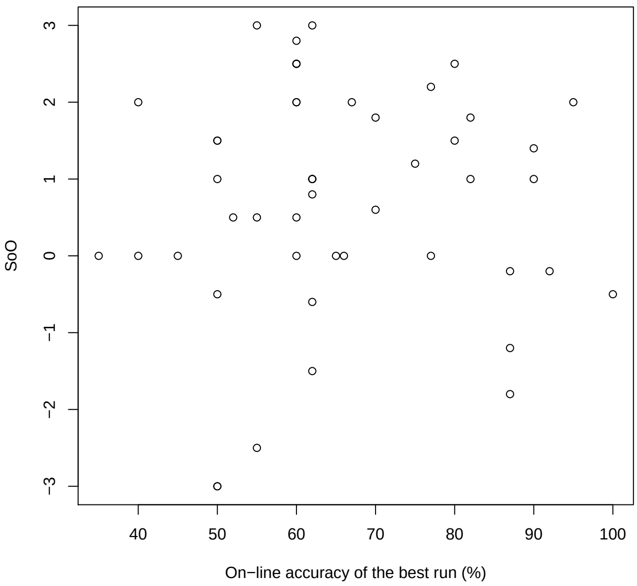

Fig. 10 The on-line BCI performance (accuracy) was not related to the perceived SoO in the session.

4.4 EEG signatures of the MI-BCI embodiment

Several EEG bands correlated to the SoO across the entire dataset from the BCI experiments, creating candidates for the embodiment EEG correlates induced by the synchrony between the imagined motor actions and congruent visual stimuli.

In the alpha frequency range, lateralized band power increase correlated to the SoO. The band power change was found only over the left hemisphere, corresponding to the right hand motor cortex (electrode C3), suggesting that the part of the cortex corresponding to the dominant hand in most participants contributed to this change in neural oscillations. In all participants, the relationship was stronger ($r = 0.452$, $p = 0.001$) than in the subset of above-chance-level participants ($r = 0.400$, $p = 0.015$).

Theta band over the sensorimotor cortex channel set was inversely correlated to the SoO ($r = -0.350$, $p = 0.017$ in all participants [$N = 49$]; $r = -0.439$, $p = 0.007$ in participants over the chance level [$N = 39$]); the relationship (all participants after outlier pruning) is displayed in Figure 11. This is an interesting result, because theta band power change is not known to correlate with the MI (on contrary to the alpha and beta bands). Moreover, the change of band power spans the whole sensorimotor channel set (it is not a lateralized effect). Still, validation in a study using other objective correlates of embodiment (such as physiological responses after stress) is required to determine

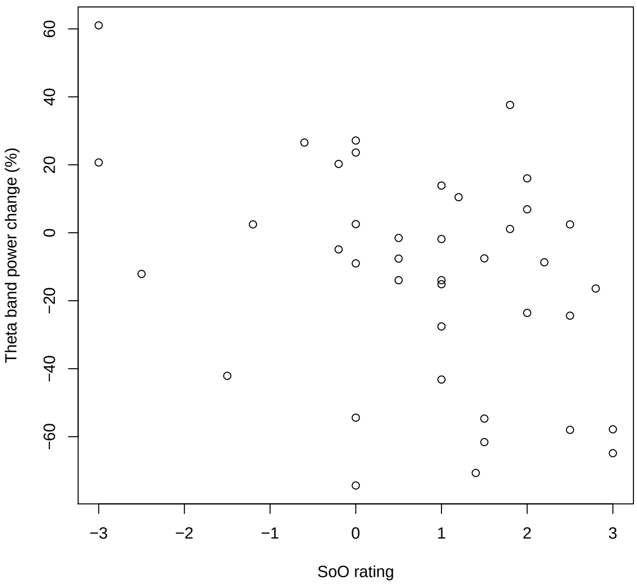

Fig. 11 Relationship between the sensorimotor cortex band power change in the theta range (in %) and the questionnaire rating of the SoO in the BCI experiments.

whether detected changes in the EEG spectra are caused by the SoO towards virtual avatar.

5 Discussion

Considering the relationship between embodiment and BCI performance, we initially expected to see a linear relationship between the SoO and performance results. The reason for that was that the SoA towards own actions is among the primary mechanisms that bind the SoO for body parts (the belief that one controls a body leads to the belief it is her/his body). Secondly, the embodiment, manifested by the SoO towards avatar, was hypothesized to facilitate the training, i.e., to allow a better BCI performance. In other words, a low performance should hinder the body ownership transfer, and a good performance should enable it; a high level of the body ownership transfer should facilitate the training, and a low level should hinder it.

It should be noted that if the SoO indeed depended on the BCI performance, a standard novice BCI user starting at a low level of performance could not leverage the hypothesized function of the embodiment in training to actually improve (a low SoO during a poor BCI control level would be hard to increase if the higher SoO required better BCI control and vice versa). However, the results indicated that the SoO was actually correlated to the SoA.

In other words, the level of the SoO did not rely as much on the performance as it did on the subjectively perceived performance in terms of avatar movements (the perceived SoA towards the BCI-controlled avatar actions; correlation displayed in Figure 8). Thanks to this relationship, the BCI-mediated embodiment could arise even in poorly-performing participants.

Our finding that the binding mechanism of the body ownership illusion was independent on control proficiency helps to clarify why the embodied VR yielded better performance results. Biased forms of feedback in MI-BCI training (feedback indicating better performance than the actual performance) have been utilized to facilitate the training process [60, 61]. Usage of embodiment seems to help participants in tackling the difficulties of the first training stages with a similar mechanism.

The analyzed data also did not contain correlation between the on-line BCI performance and the SoA towards avatar actions (which were dependent on the performance of the participant). It might be possible that the interpersonal differences in the locus of control and the self-discipline had major influences to the perceived SoA in the (single) exposure to the BCI system. This self-assessment would probably get closer to real performance after a repeated exposure (when comparison with past performances is allowed).

Correlation between the reported SoO and the strength of the ERD in MI trials provides further evidence in favor of the hypothesis that training with avatar embodiment facilitates the MI-BCI training by inducing the sense of embodiment. However, this effect was not consistent throughout the entire dataset and was rather observed only in the *Progressive* group. This can be due to the largest number of trials and the highest achieved performances (compared to the other groups), but further validation of this effect is needed. In case a link between the SoO and a correlate of the MI is confirmed in a larger study, it will provide more evidence that subjectively experiencing the avatar embodiment facilitates pre-requisites for successful MI-BCI training (such as generation of the stronger ERDs).

5.1 Limitations

Low and varying number of participants in the analyzed datasets is certainly the main limitation of this study. This limits the extent to which generalizations, especially from the between-group comparisons, can be made and calls for more studies examining the outlined phenomena with greater number of subjects. Comparisons between the groups are further weakened due to differences between the methodology of the studies analyzed. Despite our effort to compensate this issue with normalization of the data and providing explanations on differences, it must be noted that data from two, albeit closely related, studies were used in this paper.

Main disadvantage of the proposed method is the necessity to use VR equipment to mediate the BCI training. It must be taken into account that currently, the VR headsets are not suitable for overly long training sessions spanning long time periods.

6 Conclusions

With MI-BCIs, people can control devices using an interface that bypasses the motor functions of the body, but exploits them at the same time. Even if only at the imagery level, movement is still exploited in this BCI paradigm, and motor actions must be understood and well-imitated covertly to convey the control signals in the EEG representations. The problematic case when control is hindered due to an insufficient level of the imagery skills can be mitigated with the feedback that uses avatar embodiment.

Providing a better guidance could sound like a poor reason to create an MI-BCI completely enclosed within the VR, but it is important to take into account common problems with the BCI training and the target user group. People suffering from various degrees of paralysis can currently benefit the most from a well-working BCI system. Embodied MI-BCI training in VR could help the users similarly to the VR-based BCI-assisted rehabilitation – by helping to reconnect with the body and its natural motor functions.

Gamification and progressive increase of the training pace were exploited for the goals of boosting user attention and motivation, resulting in further increase of the BCI performance compared to VR alone. Moreover, the number of participants not making any progress in one session was lower in comparison to the standard protocol, and participants reported a high positive affect after the end of the session. Working with the user motivation and affect in general may be the key to the future of BCI research, as the performance results are inseparable from the effort invested by the participants.

The conditions enabling the body ownership transfer in the BCI control were much looser in comparison to the cases when motor control is used to convey one's will. The reports on the SoA towards the actions performed by the surrogate body were rather high, and they were strongly correlated to the reported SoO towards the virtual agent, suggesting a robust sense of embodiment during the MI-BCI training. At the same time, actual performance in BCI actions did not go hand in hand with the perceived agency enabled by the BCI system. As the SoO was also strongly correlated to the magnitude of the average ERD in the latter BCI experiment, it seems that employment of the embodiment could facilitate the training by a combination of the elevated SoA (similarly as in the training designs using a positively biased feedback) and the strengthened ERDs during MI when the avatar body is temporarily accepted as the own body.

7 Future work

The results provided in this work demonstrated that the first-time and inexperienced users benefit from the embodied training. The research was limited by the short overall duration of the training procedure, and it should be further researched if the VR training is feasible for longer periods of time. It is likely that the several technological limitations concerning the VR equipment (e.g., wearing the uncomfortable HMD, practical problems due to the concurrent usage of an HMD and the EEG) will be improved soon. This would increase the chances of a less demanding VR-BCI training in the near future. If the training with HMDs could be on a level of comfort comparable to the standard computer screens, the conceptual advantage of the VR MI-BCI training could easily prevail.

Nonetheless, even if the whole training procedure was mediated using VR, the typical BCI user needs to be sufficiently accurate in control of the system even outside VR. To make this transition easier, AR seems to be the perfect candidate for the future work. Embodiment in AR is by far not as much explored as the VR embodiment, mainly because AR would typically incorporate the existing body of the user. However, in the context of a BCI-mediated communication where users are typically not moving at all, this does not have to be an issue.

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