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Embodied VR environment facilitates motor imagery brain-computer interface training

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ABSTRACT

Motor imagery (MI) is the predominant control paradigm for brain-computer interfaces (BCIs). After sufficient effort is invested to the training, the accuracy of commands mediated by mental imagery of bodily movements grows to a satisfactory level. However, many issues with the MI-BCIs persist; e.g., low bit transfer rate, BCI illiteracy, sub-optimal training procedure. Especially the training process for the MI-BCIs requires improvements. Currently, the training has an inappropriate form, resulting in a high mental and temporal demand on the users (weeks of training are required for the control). This study aims at addressing the issues with the MI-BCI training. To support the learning process, an embodied training environment was created. Participants were placed into a virtual reality environment observed from a first-person view of a human-like avatar, and their rehearsal of MI actions was reflected by the corresponding movements performed by the avatar. Leveraging extension of the sense of ownership, agency, and self-location towards a non-body object (principles known from the rubber hand illusion and the body transfer illusions) has already been proven to help in producing stronger EEG correlates of MI. These principles were used to facilitate the MI-BCI training process for the first time. Performance of 30 healthy participants after two sessions of training was measured using an on-line BCI scenario. The group trained using our embodied VR environment gained significantly higher average accuracy for BCI actions (58.3%) than the control group, trained with a standard MI-BCI training protocol (52.9%).

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1. Introduction

Brain-computer interface (BCI), or brain-machine interface, is a system that records user's intents on the central nervous system (CNS) level and translates them for the purposes of controlling a computer [1]. Contrary to other input devices, BCIs do not require any muscle operation from the users. Current BCI systems can be helpful to people with a severe case of paralysis (e.g., locked-in syndrome) or rehabilitating after a stroke [2]. The most widespread devices that communicate directly with

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the brain are the neural prosthetics [3], with a well-known example being the cochlear implant, a hearing restoration tool.

Current research has limited knowledge about the inner structure and function of the human brain to create a universal BCI. Nevertheless, working examples of direct brain communication built using the current knowledge and technology exist, slowly taking the first steps out of research labs. One of the most popular BCI paradigms requires users to consciously replay bodily motor actions. This paradigm is commonly known as motor imagery (MI) [4]. MI-mediated control is dependent on the previously acquired skills, and users need to perform specialized training (spanning from tens of minutes to weeks, depending on the desired level of control) before they can use MI-BCI as





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Fig. 1. Comparison of MI-BCI training environments. Left top – example of the Graz training paradigm with symbolic instructions (indicating the user should perform right hand MI), left bottom – feedback in Graz training (indicating detected right hand MI). Right – our embodied VR training environment. Participants try to move the virtual hands by using MI of left and right hand.

a machine control interface [4]. During the training, a feedback loop is created, providing trainees with information about their neural activity. BCI trainees try to exploit this neurofeedback to find reliable mental strategies for MI. Co-adaptation between the user and the machine develops, i.e., the user gradually learns the mental strategies that create brain signals recognizable by the system, and the system learns to recognize the signals coming from the user [5].

Despite advances in the data processing and classification algorithms used in the BCI pipeline, the role of the human participant in the BCI training process was not studied to a sufficient level [6]. In case of MI-BCI, participants need to learn how to modulate their neural rhythms to grasp the control, but that is not a simple task. Common problem occurs, when the participants fail to produce adequately distinct neural patterns on the brain level, the algorithms can not efficiently extract their intents [7]. Although the chosen brain-imaging technology and its configuration influence the properties of input data in the BCI systems (e.g., by changing the density of sensor montage), the current MI-BCI systems still require the human participant to produce distinct neural patterns to correctly classify the data [8]. BCI research needs to address the issues with the training process to provide BCI users with an optimal training procedure.

Training in MI-BCIs requires the users to consciously re-play motor actions without actually executing them. This rather unnatural activity can be highly demanding when performed for prolonged periods of time [7]. Neurofeedback during the training is usually mediated by simple symbolic representation (an example of Openvibe [9] implementation is displayed in Figure 1, left). Although the feedback is necessary part of the MI-BCI training, so the trainees can be provided with the information relevant to the progress of the skill acquisition, feedback of inappropriate form can lead to distractions from the training

task [7].

In this study, the MI-BCI training process was implemented in an immersive virtual reality (VR) environment. VR allows having a more natural feedback: a human body carrying out the expected motor actions. This was achieved by creating a realistic 3D environment centered around a human-like avatar performing movements in accordance to users' advances in the MI skills, effectively creating a neurofeedback loop encoded to mimic the actual human motor actions (see Figure 1, right).

There are more benefits in transferring the training process into VR. According to [10], people can build a sense of ownership towards an avatar body in VR. Illusion of owning a foreign body part was firstly described outside VR, in an experiment known as the rubber hand illusion (RHI) [11]. In the RHI, correlated visuo-tactile stimulation (participant observes an experimenter touching a plastic hand in an anatomically congruent position, while the participant's hidden hand is touched in synchrony) leads to building of the sense of ownership towards the hand (this is discussed further in Section 2).

Similar illusion was created using the MI-BCI with the feedback delivered using human-like hands in VR [12]. If participants can build a sense of "belonging" to virtual hands during MI-BCI training, training feedback delivered through their movements could be accepted more naturally. Indeed, Braun et al. (2016) [13] studied an embodied neurofeedback using human-like robotic hand models moving in accordance with the participants' imageries, and demonstrated benefits of this type of feedback (compared to the control conditions).

Participants took part in two phases of MI-BCI training in this study. The first training phase comprised of conscious MI during observation of the motor actions performed by the avatar in VR. This phase served as a data generator for the feedback in the next stage, and it also facilitated the process of becoming embodied into the avatar's body. In the second phase, participants received an embodied feedback reflecting successfulness of their MI actions, encoded into the avatar's hand movements. After the training was finished, the participants were evaluated using on-line BCI scenario similar to the feedback training phase. In the evaluation, participants were in the direct control of the avatar's actions.

The main purpose of the current study was to develop an MI-BCI training environment leveraging the principles of embodiment, which would make the training process shorter and less tiring. This should, in turn, help the MI-BCI adoption and usability. Our hypothesis is that the embodied MI-BCI feedback would help to accept the training process, compared to the control group trained with a standard training protocol with the symbolic feedback (proposed by Graz BCI group [4]). Our assumptions are based on the past literature [13, 14, 15, 16], including our preceding study that examined efficiency of an MI-BCI system with motor action observation during the training, evaluated using a simple maze game [17] (details on this work are provided in Section 2.1).

Results from the current study indicate positive effect of the embodied training environment, in line with our hypothesis. Participants in the experimental group performed significantly better in the on-line evaluation task and also gained higher classification accuracy. The proposed VR training environment was accepted positively in the qualitative comments of participants. Moreover, the participants who became embodied into the body of the avatar reported lower levels of frustration from the task.

2. Background

Multiple definitions of the sense of embodiment exist. In this paper, we adapted the terminology from work of Kilteni et al. (2012) [18], where the sense of embodiment is used "to refer to the ensemble of sensations that arise in conjunction with being inside, having, and controlling a body especially in relation to virtual reality applications". This term is broken down to the three underlying components; the sense of self-location (experience of having a determinate volume in the space where one's body is located), the sense of ownership (SoO), and the sense of agency (SoA). SoO refers to the feeling that a body (or its part) belongs to the person, while the SoA refers to recognizing oneself as the agent of some behavior. In other words, sense that one is voluntarily causing the action [19]. Put together, the sense of embodiment towards a body is reached when the properties of that body are being processed in the same manner as if they were properties of the own body [18]. This also works for the body parts. In the RHI, the sense of embodiment is extended to incorporate a non-body object: the rubber hand [11]. The rubber hand must be placed in an anatomically plausible position, then both hands (real and rubber) are stroked by a paintbrush. Participant watches only the rubber hand while feels the touch in synchrony, which leads to incorporation of the rubber hand into own body frame. However, the original RHI experiment is only a SoO illusion. In a later experiment with a moving rubber hand, it was shown that the SoO and the SoA are distinct mechanisms; the illusion of owning a hand does not necessarily need to correlate with the illusion of being in control of the hand [20].

There are many studies examining or using the RHI as a part of the design. Experiments showed that the RHI can be replicated without a rubber hand, but using VR or augmented reality (AR) instead [21, 22]. A variation of the RHI with visuomotor synchrony was created in VR using hand tracking systems [10, 23, 24, 25]. This "virtual hand illusion" succeeds in producing the sense of embodiment toward a virtual limb, similarly as the original RHI does. Seeing an anatomically plausible hand (sense of self-location) executing motor actions in accordance with the participant's motor commands can create the illusion that the virtual hand belongs to the participant (the SoO), as well as that it obeys participant's intended actions (the SoA).

The RHI has many bodily correlates, some of which have been used to assess the strength of the illusion on an objective scale; proprioceptive drift [11] (the difference between the actual and perceived position of the stimulated hand), skin conductance change upon threat to the rubber hand [26], or neural activity in various brain regions [27]. There are studies examining the relationship between temperature of the participant's hand and subjective effects of the illusion, suggesting that the subjective RHI effects correlate negatively with the hand temperature [28, 29], while other studies fail to replicate this finding [30, 31]. Especially in [31], evidence from 5 experiments with the total of 167 participants argues against the hypothesis that the temperature drop is causal correlate of the RHI effects. In our study, we measured participants' hand temperatures to obtain a complementarily measure to the questionnaires. Proprioceptive drift cannot be measured in the virtual hand illusion (ideally, participants' hands have the same position as the virtual hands), threat to the virtual hands could negatively affect the training procedure, and neurophysiological correlates of the body ownership overlap with the correlates of MI [32].

Neurophysiological correlates of the SoA were proposed in the recent work of Jeunet et al. (2018) [33]. In their study, three distinct components of SoA were identified and manipulated separately. Resulting differences in recorded neural oscillations suggest there indeed are usable EEG correlates of the SoA. Specifically, differences were found in channels over the left fronto-central and parietal cortices, and the right temporal cortex. These findings were not available in the time of preparations of our experiment, and so the selected EEG channel setup does not allow to look for these correlates in our data. SoA questionnaire was used instead, its questions were adapted from the previous RHI study [34].

The cornerstone of the current BCIs is predominantly the electroencephalography (EEG) [8]. Despite being susceptible to the noise (both environmental and bodily), EEG is a popular choice for BCI systems due to its small size, low price, and a satisfactory temporal resolution, allowing the data retrieval process in millisecond steps [35]. The MI paradigm in brain-computer interfacing leverages the similarity between activations of the brain areas during imagery and actual execution of the motor actions. The most popular choice of imagined movements during MI are the left and right hand movements. In terms of EEG, MI of a hand is manifested as contralateral event-related desynchronization (ERD) of mu and beta rhythms

over the motor cortex [36]. Participants' task during the training for two classes of MI (i.e., motor actions using two distinct body parts) is to adapt the two mental strategies regarding the MI in such a manner that the recorded task-related neuronal oscillations become separable by the classification algorithm. Neurofeedback helps to facilitate this process. In neurofeedback, participants are being notified about correlates of their neuronal activity in such a way, that it can be enhanced in the task-specific manner [37]. In the case of training for MI-BCIs, the ERDs of participants are typically strengthened [38]. However, this process is disguised in an appropriate form of feedback, and the participants are generally not aware of the details in changes of their neural oscillations.

Standard MI-BCI training is composed of a sequence of distinct trials. The progress of a standard Graz MI training trial is as follows. Firstly, a cross is displayed on the screen to indicate the beginning of a trial and to fixate the eye position. After 3 seconds, either left or right arrow appears on the screen (Figure 1 left, top), representing the hand for MI rehearsal in the given trial. In case the feedback is delivered, it replaces the arrow on the fixation cross (1.25 seconds after the arrow is shown). Feedback usually has a form of an extending bar showing the classifier decision in the real-time, while the length of the bar indicates the confidence of the classifier [39] (Figure 1 left, bottom). The training run consists usually of 10-20 trials per class, 20 trial run lasts approximately 7.5 minutes.

Perez-Marcos, Slater, and Sanchez-Vives (2009) [12] were the first to describe the virtual hand illusion mediated by MI-BCI with synchronized visual feedback. A SoO towards a VR hand was induced in the participants performing MI while the virtual hand carried out their imagined motor action in synchrony (measured using questionnaires). High SoO for humanlike robot hands was induced using MI-BCI (measured using skin conductance response after a painful stimulus towards the non-body hand; and questionnaires) compared to the control group in [40]. In the follow up experiment, Alimardani et al. (2016) [41] compared motion tracking and MI-BCI for the control of a human-like robot. The results (measured again using both skin conductance and questionnaires) suggest that MI-BCI control brings a stronger SoO towards the robot than the motion tracking control. The illusion of owning the robot's body did not shatter even after introducing a delay to the system. This is in contrast with the older findings on the RHI, where introducing delays above 600 milliseconds strongly attenuated the illusion [42], suggesting that the BCI control can tolerate some delay and still allows the users to maintain the SoO.

On the other hand, SoA for BCI-mediated actions is weakened with delays, as well as with other discrepancies between the imagery and the outcome, similarly to the bodily actions [43]. The study argues that BCI-mediated actions rely on similar multisensory integration mechanisms as motor actions do. A difference in BCIs is that participants still maintain SoA on a high level, even when the visual feedback is incorrect, on condition that the participant cannot operate the BCI to a sufficient level. This evidence suggests that the visual feedback dominates the SoA in the MI-BCI-mediated control [43]. This is in line with another study [44], showing that participants feel the SoO and the SoA towards a virtual hand, which they think is controlled by an MI-BCI, but in fact, there is no causal link between their mental efforts and the observed hand movements. In this case, the hands simply executed the motor actions required from the participant with 80% probability, imitating the expected accuracy of true BCI actions.

Those studies examining SoA and SoO in BCI-mediated actions however performed the training process using the standard protocol. Braun et al. (2016) [13] conducted an experiment where the training feedback was delivered by means of anthropomorphic robotic hands performing the movement. Similarly to the RHI, participants' hands were kept out of sight, and similarly to the virtual hand illusion, the robotic hands were acting in synchrony with the participants' MI. SoO and SoA were measured using questionnaires and by means of the electrodermal activity after threat to the robotic hand. The validity of embodied feedback was tested by contrasting an anatomically plausible and implausible (the robotic hands rotated by 180°) condition. According to their results, 71% of the participants maintained a SoO towards the robotic hands. The experimental condition with the hand placed anatomically correctly produced faster detection of the intent by the classifier and slightly higher classification accuracy, together with stronger ERDs elicited by the participants (compared to the control group). Another study (performing part of the MI training using embodied environment) showed that the MI skills learned during the training with embodied feedback (using human-like hands) last longer than the skills learned during the feedback mediated by non-human body parts [14].

Additional support for the MI-BCI training, especially during its first stage (performed usually without the feedback), can be arranged using animations of the motor actions, displayed together with the participants MI. The fact that the human primary motor cortex is activated also during a motor action observation was first observed in 1998 [45]. In terms of BCI, this was further studied by Kondo et al. (2015) [15]. They showed video clips of grasping hands to the experimental group performing MI-BCI training, while still hands and a red/green cross were showed to the controls. Stronger ERDs were revealed in the group trained with movement compared to the control group. Similar results were obtained using a 3D visualization of the limb movements during MI tasks [16]. On the other hand, studies disproving hypothesis about strengthened ERD during motor action observation can be found as well. Neuper et al. (2009) [46] did not find a difference between a group of participants receiving symbolic feedback during training and the group instructed by videos with a hand grasping movement. Both groups showed comparably strengthened ERD in following feedback session, compared to the initial training.

2.1. Previous study - MI game

Current research presented in this paper is a follow-up on our study with an MI-BCI-controlled game [17]. Participants (N=34) were randomly assigned to one of the two following groups; either trained for MI-BCI using standard protocol with arrows (Openvibe implementation of Graz MI training) – group Arrows, or trained with a motor action observation-based training using videos of an actor raising his left/right hand (delivered



Fig. 2. Training in MI game study: a) motion observation based training (Video), b) symbolic training (Arrows).

on a 2D computer screen; see Figure 2). The training run took 7.5 minutes (20 trials per class), and the timing was identical for both groups. Only one training run was performed with the participants, and no feedback was delivered during the training session. The study was designed to show differences between the training with a help of motor action observation and the control group receiving the standard training protocol. For the evaluation purposes, a simple maze game was developed (see Figure 3). Participants were given three different levels of the game (with an increasing complexity), and were instructed to navigate the ball to the target in the shortest time possible (using the MI of left and right hand). Demographic data were collected as well, to reveal other factors influencing participants' performance (specifically the effect of gender was examined during the study). Subjective statements regarding the training and the game were collected using a set of questionnaires. Apart from the analysis of the band powers in the common EEG bands (alpha: 8-12 Hz, beta: 12-30 Hz, gamma: 25-90 Hz, delta: 1-3 Hz, theta: 4-7 Hz), engagement index (EI), an EEG correlate of engagement in the task [47], was computed (using band powers of beta/(alpha+theta) at Cz, Pz, P3, and P4 electrode locations). The EI has been used mostly in passive BCI design in the past [47, 48], and its role in prediction of MI-BCI performance is yet to be established.

The study failed to show an effect of the training modality (Video, Arrows) on the accuracy of the BCI actions (measured using the time needed to complete the game and crossvalidation accuracy on the training set). We hypothesize that the evaluation task (moving the ball through the maze) was overly different from the MI training task to produce quality results after one run of training. Firstly, participants were not allowed to practice the MI skills sufficiently before the evaluation (producing sub-optimal results overall); and secondly, the act of motor action observation could have negatively affected the training, as participants were not allowed to create their own representation of imagined movements. For further studies, it was decided to use more training time and to incorporate feedback training.

Hour of the day had an effect on the EI (MANOVA F(6,25) = 4.08, p < 0.05, $\eta^2 = 0.49$). At 3 PM, the engagement of the participants was significantly higher (mean = 0.99, SD = 1.22) compared to the other hours of the day (for each 12 PM, 2 PM, 4 PM, 5 PM, 6 PM, 7 PM the mean was bellow 0.13). However, the experimental sessions did not take place in the morning hours and the sample size of 34 participants was



Fig. 3. Participant evaluation using game (MI game study).

too small to assess the effect of the hour with confidence. We further examine the effect of the hour of the day in this paper, including the performance in the morning.

Gender did not have an effect to the evaluation results (cross-validation classification accuracy, game completion time). A difference was observed in the band power of all bands except for gamma, but this did not influence the EI significantly. Female participants reported stronger concentration on the task (Mann-Whitney U = 73.50, p < 0.05). In a separate analysis of the differences in a training group (using Mann-Whitney U test), female participants in the Arrows group rated the questionnaire metrics "How natural was the mechanism which controlled movement?" (U = 13.50, p < 0.05) and "Loss of self-consciousness" (U = 14, p < 0.05) higher (compared to Video group). Loss of self-consciousness in the Arrows group was more prominent in male participants as well (U = 91, p < 0.05).

Qualitative results (gathered in the last part of each experimental session) indicate frequent problems in understanding of the Arrows training. This happened despite the fact that the participants were explained the protocol thoroughly, and were left to try out the required MI (with the training instruction context) before the actual training began. Some of the participants did not manage to transfer the skills from the training phase to the evaluation phase (game). They often described concentration on the ball, in the sense of trying to make it move with arbitrary efforts, rather than by using kinaesthetic MI (imagining the feeling accompanied with the motor task performance [49]). Also, this issue was closely connected to the level of motivation during training and in the game. Some participants reported significant drop in the levels of motivation when the game outcome did not go as they expected.

The focus of the current study is on the training part of the MI-BCI procedure and its facilitation, using the embodied VR feedback.

3. Materials and methods

3.1. Participants

Thirty-six healthy participants were recruited for this study, and randomly assigned either to the experimental or to the control group. All the participants gave their informed consent. Five participants had to be excluded due to the technical issues during the EEG recording (either extensive artifacts in the data, or dead electrodes), and one participant failed to follow the instructions. Thus, total of 30 participants (10 female) were eligible for the analysis. None of the participants was aware that the purpose of the study was to examine the effect of VR embodiment on MI-BCI training, and did not have previous experience with BCIs. Four participants were left-handed (two per group), the rest of the sample consisted of right-handed participants. Participants were asked to attend one, approximately 90 minute long session, and participated voluntarily to the experiment. The study was approved by the Research Ethics Committee of Masaryk University with the reference number EKV-2016-057.

3.2. Apparatus

EEG data were collected using a lightweight wireless EEG device Enobio 32 [50] (the device can be seen in Figure 3) and transferred wirelessly to the computer running Openvibe [9]. Channel set-up was centered around the scalp area corresponding to the motor cortex, with 20 channels used in total. In particular, channels C3, C1, Cz, C2, C4, F7, Fz, F8, P3, F3, FC5, FC1, CP5, CP1, CP2, CP6, F4, FC2, FC6, and P4 were used in the set-up (scalp positions of the channels are visualized in Figure 4). EEG data were recorded with a sampling frequency of 500 Hz and referenced using Common Mode Sense/Driven Right Leg (CMS/DRL) electrode pair located on the right earlobe.

The VR scene was developed using Unity game engine (version 2017.1.0f3) [51]. For the delivery of the 3D scene, we used a state-of-the-art head mounted display (HMD) Oculus Rift CV1 (resolution 1080x1200 per eye, 90 Hz refresh rate, 110° field of view, rotational and positional tracking [52]). We tried to make sure that the EEG sensors are not affected by the HMD montage. Channels F7 and F8 received a pressure from the HMD plastic frame, but the rest of the electrodes were not touching the scaffold of the HMD. In-experiment signal monitoring and post-experiment signal check were used to ensure a satisfactory signal quality without extensive artifacts.

The hand motions of the avatar in the VR scene were recorded from a performance of an actor using OptiTrack fullbody motion capture system [53], the avatar models were downloaded for free from the webpage Mixamo [54], the used models are available under the names Stefani and Jimmy.

Temperature of the hands was measured using a contactless infrared digital thermometer (Cemio Metric 308 SMART). Site of the measurements was located on the back of the hand, prior the thumbs. Changes of the temperature of both hands (end of phase temperature - start of phase temperature) were used in the analysis.



Fig. 4. Scalp positions of the used EEG channels. Adapted from [55].

3.3. Setting and VR scene

During the experimental session, participants sat in a dimly lit room with their hands resting on a desk (in accordance with the avatar posture), and were disallowed any movements during the MI periods; specifically eye movements, blinking, swallowing, and hand muscle contraction during MI trials were highlighted in the instructions (movement was permitted during the rest periods between the MI trials). Regarding the instructions for the MI, the process of kinaesthetic MI was explained to the participants, as kinaesthetic MI has been shown to be more efficient than the visual MI for the purposes of controlling an MI-BCI [56]. Session consisted of three phases in the VR environment (for the experimental group) where participants rehearsed MI of the left and the right hand. Setting of the VR scene remained unchanged for all of the phases. Central element of the scene was a human-like gender-matched avatar sitting behind a desk with its hands laid on the tabletop. A red button was located ahead of the participant, approximately in the height of the eyeline. The avatar was programmed to push this button using its left and right hand. As the movements were recorded using motion tracking system, they were performed naturally first the whole arm was lifted from the tabletop, then the palm and fingers pushed towards the button, and the movement finished with the hand being put back on the table to the initial pose.

The scene contained also a TV screen located on the front wall. Its purpose was to display the instructions (details are provided in the next subsection) and progress of the experimental task. The remaining elements in the scene did not play any active role in the experiment, their purpose was to strengthen the immersion in the scene by creating a more trustworthy environment. Participants were watching this scene from the firstperson view of the avatar (displayed in Figure 1, right).



Fig. 5. Visual progress of an MI trial in the VR. Field of view provided by the HMD allowed participants to see the scene to a better extent.

3.4. Experimental procedure

The experiment had three phases: training, feedback training, and evaluation. Demo of the virtual scene was shown to the participants before the first phase. That means, the participants were shown the virtual scene (in HMD), but in the operation mode without the input from the BCI. After the participants took off the HMD, they were asked to perform conscious motor execution and MI of the avatar's movement, to gain grasp of the task before the actual training began (this is referred to as "pre-training" in literature [7]).

The training phase consisted of observation of the virtual avatar pushing the button, while participants' task was to synchronize their MI with the avatar movements. Combined MI and motor action observation is known to facilitate stronger ERD production in participants, compared to MI alone. Moreover, the participants had a chance to be acquainted with the virtual avatar's body, and to subconsciously incorporate the body and its actions into own body frame (the embodiment illusion).

In the feedback phase, participants also performed MI, but the classifier output controlled speed of the hand movements in the VR scene. When the classification result matched the currently prescribed task (left/right hand MI), the button-pressing movement performed by the avatar was carried out with the original speed. In case of being classified as the wrong class, the movements were slowed down (to a threshold value of a quarter of the original speed). The movement served as the feedback for the participant. It did not stop completely at any point, to keep the training pace stable, and to maintain motivation in the participants. Participants were informed that the speed of the movements correlate with their results, but does not stop. Consequently, the hand movement was finished to its entirety regardless of the performance in the trial. This approach was selected also to support participant motivation, as well as to prevent confusion during the training. All the trials were used for the classifier training, no matter if the participant's performance was good or bad in the trial. If the hand movements had not been completed after each trial, the different visual form of the closing of each trial could have affected the training procedure.

The evaluation phase had a progression similar to the feedback phase, but the hand movement did stop completely if the participant was unable to switch into the required mental state, as recognized by the classifier. Thus, the movement performed by the virtual hands was conditioned by the participants' successful performance. Participants were given 8 seconds to finish each trial, then a timeout occurred and the hand movement was finished. This ensured that the participants had equal conditions for the evaluation, and it is also consistent with the previous study on embodied MI-BCI feedback [13].

In each phase, beginning of the MI trial was signaled using a dot displayed on the TV screen located on the wall. After 1 second, the dot was replaced by an arrow indicating which of the hand movements is to be imagined (this procedure is illustrated in Figure 5). These symbols also served as the eye fixation points during the trials; in case there was no symbol displayed, the rest period was ongoing and the eyes did not need to be fixated. The exact timing of the trials was as follows: 3.5 second of MI followed by 5-9 seconds of the rest (the exact length of each rest phase was generated randomly) in the training phase, and 3.5-8 seconds of MI followed by 7 seconds of the rest for the feedback and evaluation phase. If the trial was finished earlier, the saved time was converted into extra rest time. Gentler pace of the training task compared to standard Graz protocol timings was chosen deliberately to minimize fatigue and stress. The values for timing of the tasks were based on the previous studies [37, 13]. Training consisted of twenty randomized MI trials for each class in the training and feedback phases (40 trials in total), the evaluation phase consisted of randomized 10 trials for each class.

3.4.1. Control group

Participants in the control group performed the former two phases (training, feedback) without the use of VR. Training instructions were delivered using the standard protocol with arrows, and feedback was displayed as extending blue bar, continuously changing according to the classifier decision (as displayed in Figure 1, left). The evaluation phase took place in the VR environment. To keep the instructions for both groups consistent, participants in the control group were shown the VR scene in the HMD before the training phase commenced. They were then instructed to mimic the avatar's movements for a couple of trials (same as the experimental group), and to perform kinaesthetic MI of this movement during the experimental phases.

Our experimental design deliberately makes use of immersive VR environment for the training purposes and the evaluation task as well; however, that resulted in having different training and evaluation environments in the control group task. It is not very common to perform MI-BCI training in a virtual environment, even in studies having the evaluation task designed in VR. Commonly, the training is done using the standard protocol (and standard computer screen), and the following task is performed in a virtual environment (e.g., [57, 58, 59], for review, see [60]). The design of this study allows to compare between the two training paradigms. As the purpose was to examine the effect of embodiment, the evaluation must have been implemented using immersive VR. However, this choice led to having two different contexts in the control group, and only one context in the experimental group. See Section 5 for a discussion on this issue.

3.5. Features and classification

The BCI pipeline was implemented using Openvibe application (version 1.3.0) [9]. EEG recordings of the MI trials (3.5 seconds long, starting 0.5 seconds after the instruction) were processed into feature vectors for the classifier training. For the feature construction process, firstly, the signal was filtered in the range 8-30 Hz (using 5th order Butterworth filter). Epochs with length of 1 second were created from the MI trials, each 1/16th of a second. Band powers of the epochs were computed using Fast Fourier Transform (FFT), and averaged in the four frequency bands: 8-12 Hz (mu), 12-16 Hz (low beta), 16-20 Hz (mid-beta), and 21-30 Hz (high beta). Weights for each of the 20 recorded channels were assessed using Common Spatial Patterns (CSP) algorithm with regularization [61]. Regularized version of CSP with Tikhonov regularization and trace normalization was applied, 3 filters for each class were computed. Finally, before using the feature vectors for classifier training, outlier detection and removal was employed, to eliminate erroneous frames polluted with high-amplitude artifacts. Outlier removal was set to prune the feature vectors containing values outside the quantile range [0.01, 0.99].

For the classification, shrinkage Linear Discriminant Analysis (sLDA) with regular covariance matrix was used. Regularized versions of CSP and LDA were used to lower the amount of training data needed for classifier training. This technique, together with the outlier removal, was adapted from the suggestions in work of Lotte (2015) [62] on MI-BCI set-up time reduction. For each phase, both CSP and sLDA were trained using the set of feature vectors originating from the immediately preceding phase.



Fig. 6. High level diagram of the experiment. Participants in the control group received visual input in the training and feedback training phases using a standard computer screen instead of the HMD.

3.6. On-line processing

The feedback in VR training (i.e., speed of the avatar's hand movement) was controlled by the classification results, which were tested each 1/16th of a second. Data transfer from Openvibe to Unity was implemented using the built-in Virtual Reality Peripheral Network (VRPN) server and Unity Independent VRPN Adapter (UIVA) [63]. VRPN is a library designed to help with the process of connecting various VR software and hardware together. UIVA is the layer that allows Unity to connect to the VRPN server. High level diagram of the data flow between the components of the experiment is shown at Figure 6.

3.7. Training score computation

On-line accuracy of each participant (score) was computed during the evaluation phase of the experiment. Score was calculated for each trial separately. In the trial, it refers to the percentage of time the classifier recognized the desired mental pattern for the current MI task. Scores of individual trials were averaged over the experimental phase. Score was computed in the VR experimental application, thus in the experimental group, it is available also for the feedback training phase.

The advantage of computing the scores is that we obtained a practical measure and did not have to rely on the cross-validation classification accuracy only. However, crossvalidation accuracies of the training sets of each participant entered the analysis as well, Openvibe LDA trainer (with 5-fold cross-validation test) was used to gather these values.

3.8. EEG data processing

The EEG recording datasets were visually inspected for artifacts, recordings of unsatisfactory quality led to rejection of 5 participants. ERD of each recording was calculated using event-related spectral power (ERSP) averaged over the frequency range of interest, i.e. 8-30 Hz. For the purposes of analysis, channels C3 and C4 were selected to produce two ERD

Questionnaire					
SoA	(1) I felt as if I was controlling the movements of the virtual hands.				
	(3) I felt I was controlling the virtual hand movements by thinking of moving my left or right hand.				
SoO	(2) I felt as if the virtual hands were my hands.				
	(4) I felt as if the virtual hands were part of my body.				
Proprioception	(5) I remained aware of the position of my own hands.				
SoA control	(6) I felt as if my hands moved whenever the virtual hands were moving.				
SoO control	(7) Sometimes, I felt as if I had more than two hands.				
Interviews					
Training	(1) Was it easy for you to imagine the given hand movement after the instuction was shown?				
	(2) Was it easy for you to concentrate on the hand movement that you should have performed?				
Feedback	(3) Do you think that the feedback helped you?				
	(4) Was the feedback annoying sometimes?				
Evaluation	(5) Did you imagine the movement the same way all through the tasks or did your mental strategy change?				

Table 1. Questionnaire and interview questions.

courses (for the actual experiment, CSP determined weights of the channels); C3 for the right hand, C4 for the left hand. The ERSP (log power) was computed relatively to the baseline of 1500 ms before the set of relevant MI trials (20 trials for each hand in the each of the training and feedback phases, 10 trials for each hand in the evaluation), baseline mean value was removed before the computation. These ERD courses were averaged over the trials of each participant, and entered the analysis as the percentage change of in- versus pre-trial band power.

Grand ERD averages for each condition and group are visualized in Figure 7. We also computed engagement index (EI), the chosen EI consists from the band powers of beta/(alpha+theta), calculated from the centro/parietal channels (Cz, P3, P4, CP1, CP2), in the second half of the task (recording) course [47]. All the analyses were done using EEGLAB (version 14.1.1) [64] and MATLAB (version R2015b) [65].

3.9. Questionnaires and interviews

Short interview followed each experimental phase, and two questionnaires were handed out to the participants before the end of the experimental session.

NASA Task-Load Index (TLX) was used to assess the cognitive workload of the participants. NASA-TLX consists of 6 questions on 21-point scales; mental demand, physical demand, temporal demand, performance, effort, and frustration. The second questionnaire was designed to examine participants' SoA and SoO towards the virtual hands and awareness of the position of own hands (proprioception) during the VR task (see Table 1). Answers were positioned on the Likert scale (ranging from -3: total disagreement with the statement, to +3: total agreement with the statement). Results of the individual questions were averaged across the following categories; questions 1 and 3 produced the SoA rating, questions 2 and 4 produced the SoO rating. Proprioception, control statement for SoA, and control statement for SoO correspond each to one question; 5, 6, 7, respectively. Results from the category of SoO questions were used to form the group "embodied participants", specifically, this group contained all the participants who rated the SoO >= +1. This criterion was adapted from the previous study [13].

The purpose of the interviews was two-fold. Firstly, answers to the designed interview questions were gathered (the questions are present in Table 1). They were aimed at examining the participant's self-evaluation of the work with the MI (2 questions after the training phase), usefulness of the feedback (2 questions after the feedback phase), and changes in the mental strategy (one question after the evaluation). Secondly, qualitative comments on the experimental phases were collected (qualitative comments were gathered also using a written form after the experiment). The designed questions were assessed on a reduced Likert scale (with steps: "no", "rather no", "unsure", "rather yes", "yes").

4. Results

Statistical analyses were run on the collected data with the three main aims:

- 1. To determine the effects of the group (experimental/control) and the perceived embodiment (embodied participants)
- 2. To examine the correlations between score, crossvalidation accuracy, and the subjective feedback (questionnaires and interviews)
- 3. To examine the hour of the day, gender, hand temperature, and EI effects

Mann-Whitney U test was used to examine the effect of the group, Spearman correlation (r_s) was utilized to find correlations in the data. Significance level of p < 0.05 was chosen.

4.1. Training score

The results showed a higher score for the experimental group, receiving the embodied VR feedback during the training (group average 58.30%, SD = 6.38%), compared to the control group (group average 52.91%, SD = 5.87%). Results from Mann-Whitney U test revealed a significant difference between the

scores of the two groups (U = 42, p = 0). Perceived embodiment did not have significant effect on the score; embodied participants gained higher average score (56.97%, compared to 54.24% in the control group), but the difference was not significant (U = 87, p = 0.29).

The mean score in the feedback phase of the experimental group was 55.67% (SD = 6.62%). This score predicted the performance in the evaluation phase (Spearman correlation; N=15; $r_s = 0.80$, p = 0), and the score increased between the feedback and the evaluation phase of the experimental group in 12 cases. Drop was observed in two cases, and in one case, the score stayed unchanged.

4.2. Cross-validation accuracy

The chance level of the cross-validation accuracy in the feedback phase was determined using binomial cumulative distribution [66] on a significance level of p < 0.05, and equaled 63.33%. Total of 70% of participants exceeded the chance level (73.33% in the experimental group, 66.67% in the control group). Average cross-validation accuracy of the participants exceeding the chance level equaled 71.30%.

Comparison with the obtained scores provided some additional insight into the relationship between the cross-validation accuracy on the training set and the performance in the on-line task. There were significant correlations between the feedback phase cross-validation accuracy and the feedback phase score (computed for the experimental group only; N=15, $r_s = 0.70$, p = 0), and the cross-validation accuracy in the feedback phase and the evaluation phase score (for all participants; N=30, $r_s = 0.46$, p = 0.01). This was true even for the relationship between training phase cross-validation accuracy and score $(r_s = 0.43, p = 0.02)$. Cross-validation accuracy of participants in the training phase correlated with the feedback phase accuracies ($r_s = 0.47$, p=0.01). Nevertheless, all the values for the cross-validation accuracy were much higher than the follow-up real performances - score (feedback phase, experimental group mean = 69.60%, SD = 7.42%; control group mean = 67.13%, SD = 5.79%).

Difference between cross-validation accuracy of the feedback training and the evaluation phases was evaluated as well. Participants gained higher accuracy in the evaluation than the feedback training phase overall, but the difference is very small (3.57% in average, experimental group: 3.87%, control group: 3.27%). Drop of cross-validation accuracy between phases was observed in 3 cases in the experimental group and 5 cases in the control group.

4.3. ERD analysis

Analysis showed that all participants in the experimental group produced ERD in the observed range 8-30 Hz during the on-line task (based on the average ERD in the experimental phase), and two participants in the control group failed to produce ERDs during the evaluation phase. The average ERDs during the right hand MIs are visualized in Figure 7 (the right hand ERDs were more prominent than the left hand ones). Spearman correlation test confirmed the expected (positive) trends between the ERD strength and the score, even if there was no significant correlation ($r_s = 0.27$, p = 0.14). Participants in the experimental group had stronger average ERDs compared to the controls in all of the experimental phases, but the effect was not statistically significant in any of the phases (for the evaluation phase, Mann-Whitney U = 105, p = 0.76). Similarly, the effect of embodiment on the ERD strength (group "embodied participants") was not significant (U test for the evaluation phase; U = 73, p = 0.10), but the average ERD was stronger for the embodied participants in all of the experimental phases. Interestingly, gender of the participant had a significant effect on the ERD strength in the evaluation phase (Mann-Whitney U = 25, p = 0), with the female participants producing more prominent ERDs (true for all of the experimental phases). Nevertheless, it is not possible to draw conclusions from this evidence, as the sample was not balanced in terms of the gender (10 females, 20 males).

4.4. Sense of embodiment

Results for both SoO and SoA statements (positioned on a scale from -3 to +3) were comparable across the groups. Mean SoA rating was 1.40 (SD = 1.28) (indicating a positive SoA towards the virtual hands actions), whereas mean SoO was equal to 0.70 (SD = 1.67) thus near the middle of the scale. SoA was slightly higher in the experimental group (mean = 1.57, SD = 0.86) than for the controls (mean = 1.23, SD = 1.61). Mean SoO was higher for the controls, but with a very low difference (experimental group mean = 0.63, SD = 1.52; control group mean = 0.77, SD = 1.86).

The embodied participants group (giving the SoO rating higher than or equal to +1) consisted of 15 participants, with the distribution balanced across the groups (7 participants in the experimental group, 8 participants in the control group). This suggests that the previous VR experience during the training did not affect the ratings in the evaluation phase of the experiment. Similar tendency is present for the agency statements. The ratings equal or higher than +1 were given by 12 and 11 participants for the experimental, control group, respectively.

Mann-Whitney U test between the embodied participants and the rest of the sample revealed the effect of high embodiment on two variables: the ratings of SoA (U = 44, p = 0), and the ratings of frustration (U = 51, p = 0.01). The embodied participants felt stronger agency for the movement of the virtual hands (mean = 2.07, SD = 0.80; non-embodied: mean = 0.73, SD = 1.35), and they reported less frustration in the end of the experimental session (NASA-TLX; mean = 2.93, SD = 2.57; non-embodied: mean = 6.13, SD = 3.87).

Gender had an effect on the SoO statements. Females reported significantly (U = 46.50, p = 0.02) higher ownership of the virtual hands (mean = 1.70, SD = 1.06) than males (mean = 0.20, SD = 1.71).

The mean answers for both control questions for SoO and SoA statements are below zero. The SoO control question was rated more negatively by the subjects in the experimental group (-1.80 versus -1.20) and the SoA control question was rated more negatively by the controls (-1 versus -0.60). However, negative correlations between SoO and SoA, and their corresponding control questions were not confirmed (SoO and SoO



Fig. 7. Grand average of the ERD time courses – the experimental (solid blue) versus the control (dotted red) group in each phase of the experiment (top: training, middle: feedback, bottom: evaluation). The ERDs were calculated by averaging ERSP of the right hand MI over C3 channel and the 8-30 Hz frequency band for 15 participants and 20 trials (training and feedback) or 10 trials (evaluation). Cues for the MI trials were presented at time = 0, and epochs from 500 ms to 4000 ms were used to produce the feature vectors.

control $r_s = 0.27$, p = 0.15; SoA and SoA control $r_s = 0.04$, p = 0.82).

No significant correlations were present for the score results and SoO ($r_s = 0.20$, p = 0.30) and SoA ($r_s = 0.20$, p = 0.28) statements gathered via questionnaires.

4.5. Interviews

No significant between-group differences were found in the interviews. Non-significant difference was found between the experimental and the control group answer to the interview question (1), asking how easy it was to imagine the hand movement during the training. Positive (median "rather yes") answer was predominant in the experimental group, and negative ("rather no") in the control group (U = 73.5, p = 0.10). Another non-significant difference between the groups was revealed in the questions regarding change of the mental strategy (U = 75.50, p = 0.09). Participants in the control group reported change of strategy less (median answer "rather yes") than participants in the experimental group (median answer "yes").

4.6. Other results

Positive correlation was found between the evaluation phase EI and score ($r_s = 0.44$, p = 0.02), with no effect of embodiment, nor selection of the group.

The expected temperature drop was observed in 56.67% participants (temperature did not change in 36.67% of participants). However, the change did not correlate with the SoA or SoO ratings, nor with the score in the last phase of the experiment.

An effect of the hour of the day was not confirmed in this study. Although participants scored best in the morning hours (10 AM-12 PM; mean = 58.40%, SD = 9.43%), compared to the afternoon time slot (2 PM-4 PM; mean = 54.51%, SD = 5.98%), and the evening (6 PM-8 PM, mean = 54.33%, SD = 3.95%), the scores did not differ significantly between those times. However, the data were not balanced across the time slots.

The qualitative comments gathered in the questionnaires and during the interview were mostly concerning the symbolic feedback, 4 participants claimed it was distractive, and 3 participants described it as confusing. That implies that out of 15 participants receiving this kind of feedback, nearly a half of them commented on the symbolic feedback negatively. The interviews also revealed that some of the participants were having problems to perform kinaesthetic MI in the first phase of the experiment, especially those from the control group. Overall, the acceptance of the experimental session was high (qualitative comments); in terms of the quantitative data, the average frustration rating was equal to 4.53 (median = 4, SD = 3.62) out of 21 points (NASA-TLX).

Other results from NASA-TLX indicated positive correlation between the evaluation phase EI and both self-reported performance ($r_s = 0.39$, p = 0.03) and the temporal demand of the task ($r_s = 0.39$, p = 0.03).

5. Discussion

This study examined the effect of VR embodiment on MI-BCI training. The traditional MI-BCI Graz training protocol with a symbolic feedback was compared to a VR training environment with an embodied feedback, designed for the purposes of this study. Results confirm that the participants who performed training in the VR environment performed significantly better in the final evaluation, compared to the control group trained with the symbolic instructions. To our knowledge, this is the first study with the aim to directly compare the common Graz MI-BCI training to a new paradigm leveraging the principles of embodiment. Previous studies utilized motor action observation followed by embodied feedback in training, similarly to this study; however, their focus is on validity of the embodied feedback. The feedback using human-like body parts was contrasted to a control condition with incorrect (anatomically implausible) feedback [13, 40, 14]. Our study goes further, trying to prove that a replacement of the traditional MI-BCI training protocol by an improved one, using meaningful visual feedback, increases the usability of such MI-BCI (in terms of performance).

Due to comparison of the two different training procedures in the experimental and control group, it is not a simple task to isolate the effect of the VR environment (and embodiment) on the results. Of most concern is the context of training and evaluation in each of the groups. To evaluate the effect of different training modalities on the results, we chose to employ the same modality (VR) for the evaluation of the both groups. This resulted in difference between contexts in the experimental and control group. Specifically, the whole task was carried out in VR for the experimental group, but both standard display and VR was used in the control group. This could have led to utilization of different cognitive/neural mechanisms during the training and evaluation tasks, theoretically leading to worse performance in the evaluation for the control group. We argue that this effect is probably not very strong, as in most of the cases, cross-validation accuracy between the last training phase and the evaluation phase did not change much (the differences are comparable for both experimental and control group).

Another point that needs to be taken into account is the number of participants in this study. BCI studies are traditionally of small-sized samples (see e.g. [12, 13, 23, 59, 46], where the number of participants is lower than or equal to 25), mainly due to difficult and time-consuming procedure and relatively high ratio of discarded participants due to the signal recording issues [67]. In this study, we opted for relatively high number of participants among the BCI papers. On the other hand, equal initial conditions of the participants were not ensured, in terms of MI skills. Random group assignment should alleviate the effect of disbalanced initial conditions; however, to be sure that the random assignment eliminates the problem, the sample size should be higher. This needs to be borne in mind when interpreting the results.

The aforementioned issue is reflected in the recorded EEG data. The analysis revealed large variations across the participants' ability to produce consistent changes in their neural rhythms during MI. After averaging the lateralized ERD timecourse for all the participants in the group, the decrease in the band power is clearly visible in the plot, as well as the differences between the groups (Figure 7). High variability in the ERD strength probably accounted for the non-significance in the statistical testing for the effects of group on the ERD strength. The between-group difference in the ERD strength (i.e., in the spectral power before and during the MI trial) for the training phase (where no feedback was presented yet) can be observed clearly from the ERD grand average plots. It therefore seems that motor action observation indeed has an effect on the initial ERD production during MI, helping to generate more quality data for the initial classifier training. On the other hand, the ERDs obtained in the last phase of the experiment clearly are not generated by mere motor action observation, as the motor actions of the avatar were conditioned by successful MI in the evaluation phase.

An objective of this research was to study the level of embodiment into the body of a virtual avatar. Markedly positive SoO was subjectively felt by 50% of the participants (without an effect of the assigned group). This suggests rather weak induction of the rubber hand-like illusion using the virtual hands. Closer look at the group of the embodied participants shows that they gave a significantly higher SoA rating to the experimental environment and had non-significantly higher evaluation score. Therefore, although we can not confirm the influence of the perceived SoO on the score, the stronger feelings of ownership towards the virtual body go hand in hand with the agency towards the BCI-mediated actions. Potential aim for the future work occurs; development of VR environments that allow more people to be immersed into, and consequently to become embodied to the associated avatars as well. This will allow more detailed exploration of the effects of embodiment to MI-BCI performance.

Our results suggest that the chosen training modality influences the performance more than the subjective level of embodiment does. The VR training environment can facilitate more rapid training resulting in a higher evaluation score after two phases of training. Although some of the participants were immersed to the body of the VR avatar, that was not the critical factor for the higher score. After the training for MI-BCI in the virtual environment, even the participants who did not feel ownership of the avatar's body in the evaluation phase scored better than the participants trained with symbolic training. In general, performance in MI-BCI is affected by number of factors falling into category of the personality profile and cognitive traits of the user [68]. An important aspect may be the locus of control (personal belief in the degree of controlling the outcomes of the events in her/his life), that has been shown to correlate with the MI-BCI performance [69]. In similar fashion, the gathered SoO and SoA values might be influenced by the personality of each participant, as they were collected by questionnaires. The effect of the embodiment needs to be studied more thoroughly. Higher score after the VR training may be simply caused by an improved visual appearance used for the feedback presentation. The training process was facilitated by encoding the feedback into the actions of the avatar - no matter if the participant actually became embodied into its body, or not.

The broad topic of improvements to the MI-BCI training pro-

tocol is discussed in the work of Lotte et al. (2013) [7]. We decided to adapt some points that were applicable to the design of our study; e.g., giving the periods of pre-training to participants, providing a positive-only feedback in the training. It has been shown that the first stages of training benefit from positive feedback only [70]. The feedback in the VR training environment should also induce feelings of competence in participants, directly influencing the motivation in a positive way, as suggested in [71]. The VR training environment design allows to blur the line between the training and the subsequent application of an MI-BCI system - the training environment can be only slightly modified to become an application environment for a desired BCI task [7]. Avatar is the only necessary element of the scene, the rest might change according to the real-word application needs. On the other hand, even complementary approach could bring interesting results - testing the persistence of skills learned during the embodied VR MI-BCI training in further sessions, without the use of VR. After sufficient amount of training is completed, feedback is not really necessary for the participant, and it is possible that the VR encapsulation could be removed without causing a drop in user performance (accuracv).

We did not establish the link between the temperature drop in participants' hands and the reported SoO. This is in line with [31], showing evidence against cooling of the hands during the RHI. Our work supports this evidence for the case of the MI-BCI-induced virtual hand illusion.

Development of more immersive VR training environments is necessary for the future of this research direction. The hand movement in the training and evaluation tasks was chosen based on the high number of muscles engaged in the execution, its range (and associated duration), and the continuous nature (allowing continuous MI feedback, which has been shown to be more effective for learning [72]). On the other hand, it can be argued that movements incorporating the hand only (i.e., fingers, palm; without an arm movement) could produce a higher SoO, as the overall bodily position would change less. Higher resemblance to the original RHI would be kept as well, as participants do not move at all in the RHI, and to produce the illusion, only their fingers are stimulated with touch.

6. Conclusions and Future work

We presented a novel embodied VR environment for MI-BCI training based on a gender-matched human-like avatar carrying out motor actions in synchrony with the participants' MI. The hand movements of the avatar serve as a feedback on MI trials, guiding the user throughout the training process, instead of the symbolic visual guidance commonly used in the MI-BCI training protocol. To validate the method, user study (N=30) was conducted; the experimental group performed embodied VR training for MI-BCI (N=15), while the control group performed the training using standard Graz protocol (symbolic instructions on a standard computer screen).

Results indicate better acceptance of the embodied VR training. Participants in the experimental group gained significantly higher score (actual accuracy calculated on-line in the evaluation phase of the experiment). Our VR training environment is based on the principles of embodiment into a VR avatar's body, to facilitate consistent learning of the MI skills in new trainees. Significant results in terms of objective measures were gathered despite the fact that not all of the participants in the experimental group felt a strong sense of ownership towards the virtual hands that mediated the training.

In the future, we will create more virtual training scenarios (3D scenes). Left and right hand MI will be kept, but the visual instructions will be composed of various different hand motions throughout the training session. This could potentially bring more robust learning [73, 7]. Multimodal stimulus presentation has been shown to be beneficial for MI-BCI training as well. VR environment enriched with haptic feedback produced promising results in terms of the classification accuracy during the initial training session for MI-BCIs in the work of Vourvopoulos et al. (2016) [74]. Although SoO and SoA were not studied, the training modality helped in acceleration of the training with mechanisms similar to this work.

Most importantly, the next steps in the research on embodied MI-BCI training must follow the needs of the participant in the training process, mainly addressing the issue with a decreasing motivation. Even though the VR environment created for this study was more engaging to the participants than the symbolic training modality, the training still lacked any engaging tasks to follow. Next iteration of our training environment design will be inspired by games and will incorporate game-like tasks and visible score keeping. This, together with breaking from the steady pace of the training procedure in favor of more user-oriented approach, promises to significantly reduce the training time for the future MI-BCI users. [68, 60].

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