Reducing Brain-computer Interaction Training Time with Embodied Virtual Avatar

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Keywords: Brain-Computer Interfaces, Gamification, Motor Imagery, Sense of Agency, Virtual Embodiment, Virtual Reality.

Abstract: Brain-computer interfaces (BCI) have been intensely researched to provide a method for controlling computers, robots, and other machinery using mental activity only. Nevertheless, BCIs remain difficult to use in everyday life. One of the major BCI paradigms, the motor imagery (MI), showed improved control performance when avatar embodiment in virtual reality (VR) was exploited in the BCI system. Control accuracy was further increased with gamification of the MI-BCI training procedure. This paper presents comparative study of 3 types of MI-BCI training: with the standard protocol, mediated using a virtual avatar, and in a gamified, embodied setting with progressive increase of the training pace. Overall analysis of the relationship between embodiment and BCI performance showed robust embodiment illusion supported by correlation between the sense of ownership towards the avatar and the sense of agency towards the BCI actions. Interestingly, the actual control proficiency was uncorrelated to the perceived performance and to the sense of ownership. This could work towards facilitation of the initial training steps similarly to designs exploiting positively biased feedback.

1 INTRODUCTION

Brain-computer interfaces (BCI) have been subject of intense research during the last decades, yet there are numerous issues with their practical applications. Virtual reality (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* (Slater, 2009) – 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* (Graimann et al., 2010). 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 interface for computers, robotics, and general machinery. Healthy users can leverage BCIs for monitoring of affective and cognitive states (Mühl et al., 2014), e.g. for using information about estimated level of invested attention as additional input for computer games or meditation training (Kerous et al., 2017).

This paper presents results on research of brain-computer communication facilitated using avatar embodiment in VR. The main purpose of combining BCI and VR was to facilitate the training task for BCI communication (imagery of hand movements) with adequate feedback (hand movements performed by the surrogate body in VR). This research is focused on the BCI communication paradigm based on motor imagery (MI, MI-BCIs), which exploits changes in neural activity generated by consciously attending to bodily movements.

The aim of this study was to investigate the advances in user training for MI-BCI usage by leveraging embodiment and gamification in VR. Data from 3 groups of participants taken from 2 previous experiments (Škola and Liarokapis, 2018; Škola et al.,

Škola, F. and Liarokapis, F.
Reducing Brain-computer Interaction Training Time with Embodied Virtual Avatar.
DOI: 10.5220/0011049100003124
In *Proceedings of the 17th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2022) - Volume 1: GRAPP*, pages 7-17
ISBN: 978-989-758-555-5; ISSN: 2184-4321

2019) which were part of a bigger study on embodied VR MI-BCI training (Škola, 2020) were studied a) to investigate the hypothesis that VR embodiment aids the MI-BCI training procedure (reduces the required training time), and b) 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 user's imagined movements as the input and using the movements of the "surrogate" avatar body as the output). Finally, the third group was trained with a gamified VR application with avatar embodiment. In the simple game wrapped around the training procedure, participants were trained using a more visually appealing and engaging environment. Moreover, progressive increase of the training pace was incorporated.

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

Control strategy in MI-BCIs consists of focused imagery on movement of own hands, feet, etc (Lotte et al., 2015), mediated by user modulation of the sensorimotor rhythm in the brain. Although most people have some sensorimotor rhythm modulation ability (Dickhaus et al., 2009), training is typically needed to achieve a reasonable level of control accuracy. The training has usually a form of repeated trials where users perform the MI process of specified body parts, followed by immediate visual feedback from the system, allowing users to understand if their MI effort was recognized successfully. One of the goals of the training is to enhance the ability to create a distinct pattern of neural rhythm change during the imagined movement, called event-related desynchronization (ERD), in motor cortex parts associated to the imagined body parts (Kaiser et al., 2014). This consequently improves the prediction capabilities of the machine learning side of the BCI system (Lotte et al., 2015). The training process is a co-adaptation; while the user is trained with the help of neurofeedback, the classifier in the BCI is trained as well (Lotte et al., 2015).

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 is shown concurrently with the MI process, leading to attention split between comprehension of the feedback and focusing on movements of the body.

BCI research recently started to highlight the importance of the human-facing side of the interface (Lotte et al., 2013; Jeunet et al., 2016a; Jeunet et al., 2016b; Kosmyna and Lécuyer, 2017; Sollfrank et al., 2016). Main criticism considered the standard training protocols, for the reasons they ignore elementary psychological findings about the optimal forms of training (e.g., using progressive or adaptive task design, exploiting rich feedback modalities (Jeunet et al., 2016b)). 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" (Deterding et al., 2011). In the BCI context, gamification is helpful especially as it aims to improve immersion and motivation (de Freitas, 2011). BCIs are often used as game input interfaces, both for training or other research purposes (Kerous et al., 2017).

Past research has demonstrated that the visual representation of the self in VR can be utilized to facilitate the BCI control (Salisbury et al., 2016; Vourvopoulos and Bermúdez i Badia, 2016; Vourvopoulos et al., 2019; Škola and Liarokapis, 2018; Škola et al., 2019). The virtual agent is usually called *avatar* and the subjective experience of having and being inside a virtual body *virtual embodiment* (Kilteni et al., 2012). Human brain has special mechanisms for recognition and self-attribution of the "attached" body, using prior knowledge and the available sensory data (Jeannerod, 2003). In VR, the visual contact with own body is cut off and replaced by the rendering of the avatar. First person view of a body that acts in accordance with one's will creates a strong embodiment illusion, including 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 (Meehan et al., 2002).

When the body is self-attributed, one experiences what is termed the sense of (bodily) ownership (SoO) (Gallagher, 2000). The sense of being the author (agent) of the voluntary actions is termed the sense of agency (SoA). The SoA can be defined in terms of the authorship of the voluntary move-

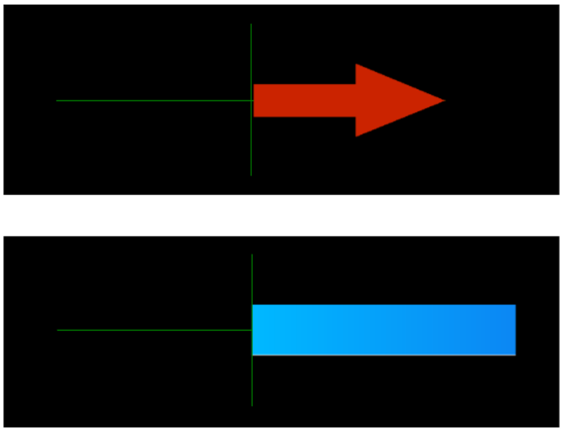

Figure 1: Openvibe implementation of the Graz training protocol (symbolic guidance); top: instruction to perform a right hand MI trial, bottom: feedback (an extending bar) representing a relatively confident classifier decision that the current participant's mental effort belongs to the right hand MI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

ments (Blanke and Metzinger, 2009), but more commonly the definition includes also the covert actions such as creating an intent or a thought in the stream of thoughts (Gallagher, 2000; Gallagher, 2007). BCIs allow manifestation of one's SoA using covert actions; i.e., BCIs allow for translation from the intention to an action without any movement.

3 METHODS

3.1 Compared Variables

Embodiment was quantified using questionnaires on SoO and SoA (standard questions from studies on body ownership were used, based on (Botvinick and Cohen, 1998; Longo et al., 2008)), answered on a Likert scale from -3 to +3, after the experiment. BCI performance was calculated as a) total time spent in the correct MI state (recognized by the classifier) and b) percentage of successfully recognized MI actions (a normalization between study (Škola and Liarokapis, 2018) in Section 3.2 and the study (Škola et al., 2019) in Section3.3 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. 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) obtained and analyzed.

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

3.2 Study Comparing Standard and Embodied Training

The first study leveraging embodied VR training for MI-BCI (Škola and Liarokapis, 2018) 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 was necessary 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 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 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 signals are prone to artifacts, generated either by both bodily and 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 signals with brain signals originating from the activations in the motor cortex.

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 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 (Kondo et al., 2015), further facilitating the initial training step.

The proposed embodied training aimed to correct sub-optimal elements of the training procedure, especially the feedback modality (incomprehensive guidance causing split between the task and the provided feedback), touching the motivational aspects of the training. The main feedback method was using 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 stopping) indicated problems of the BCI system to comprehend the user EEG inputs.

From the 30 participants in this study, control group (N = 15) was trained using the Graz training protocol (Openvibe implementation) on the standard computer screen, while experimental group (N = 15) was trained using the novel embodied protocol. 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 (Škola and Liarokapis, 2018) for a detailed information on the study.

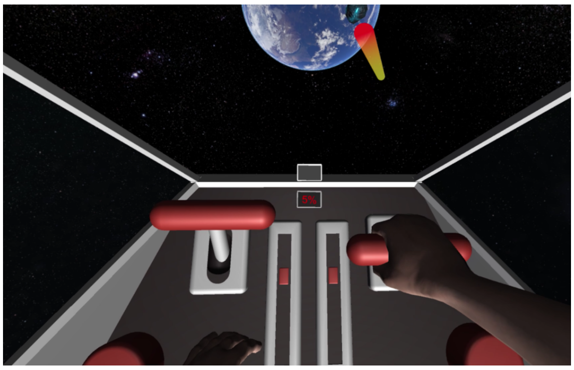

Figure 3: VR feedback representing a recently finished right hand MI trial in the *Progressive* group.

3.3 Study using Gamification and Progressive Pace for Training

The novel VR application created as a gamified variant of the MI-BCI training (Škola et al., 2019) kept most from the standard trial-based form of the MI-BCI training (randomized training trials grouped into several stages, with given cue before each trial, and randomized rest period after each trial). Gamified training employed themed environment and score points, while the challenge in the game arose mainly from the progressive increase of the speed across several training runs, or levels (categories of motivational affordances were adapted from (Hamari et al., 2014)). Feedback on user progress was provided using three modalities:

1. Embodied feedback mediated by the speed of avatar hand movements (real-time)
2. "Score" displayed in the VR scene (post-trial quantification of the trial accuracy)
3. Vibrotactile feedback to the corresponding hand mediated by the VR controllers (real-time)

The VR scene was set in the outer space, the participant was 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.

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, 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 (Škola et al., 2019).

The VR training environment was evaluated in a between-subject user study with 19 participants (N = 20 including a participant falling below 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).

3.4 Compared Groups and Results

The following 3 groups are analyzed in this paper:

- From the user study comparing the embodied VR training to the standard method (Škola and Liarokapis, 2018)
  - *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 (Škola et al., 2019)
  - *Progressive/Gamified* group (participants trained with embodied avatar in gamified, progressive VR)

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 (Škola and Liarokapis, 2018), the on-line accuracy was reported as an average of percentages of time in each trial spent in the correct MI state. On-line accuracy metric called "hit-wise accuracy" (percentage of trials with $>50\%$ successful time) was used in (Škola et al., 2019), representing the percentage of successfully issued commands using a two-class BCI. In comparison to the accuracy metric from (Škola and Liarokapis, 2018), 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 "hit-wise accuracy" was utilized for the overall analysis, and all the performance results from (Škola and Liarokapis, 2018) were recalculated for purposes of this paper.

4.1.2 Differences between the Accuracy Metrics and the BTR

In (Škola and Liarokapis, 2018), 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%.

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.

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

Group	N	Accuracy (run 3)	Accuracy (best run)	BTR (run 3)	BTR (best run)
Control	7	62.286% (8.655)	62.286% (8.655)	0.267 (0.396)	0.267 (0.396)
Embodied	13	65.385% (16.132)	67.153% (14.960)	0.700 (1.306)	0.728 (1.292)
Progressive	19	67.105% (10.603)	75.842% (11.251)	0.825 (0.949)	1.992 (1.992)
Control (w/s-ch-l)	15	53.067 % (11.386)	53.067% (11.386)	0.160 (0.288)	0.160 (0.288)
Embodied (w/s-ch-l)	15	63.333% (15.886)	64.867% (15.109)	0.606 (1.234)	0.631 (1.223)
Progressive (w/s-ch-l)	20	66.250% (11.007)	74.400% (12.709)	0.784 (0.942)	1.893 (1.606)

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).

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

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 4 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

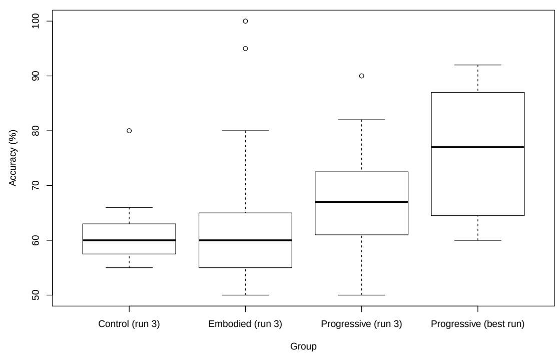

Figure 4: Boxplots showing per-group BCI performance (accuracy).

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).

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.

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.

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

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

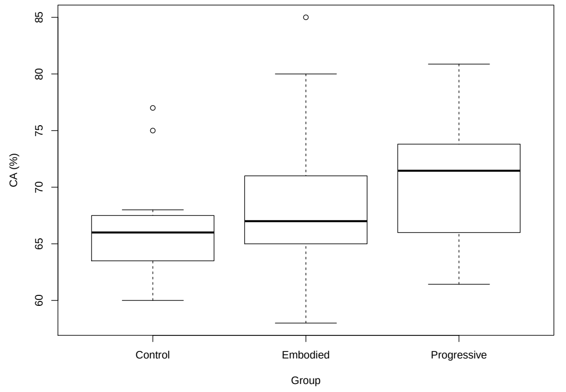

Figure 5: Boxplots showing CCA of the dataset corresponding to the initial training. The results are shown per training method, without the sub-chance-level participants.

the CCA in the first run (see Figure 5). This CCA represents the initial ability of the classifier to distinguish between the classes based only on the feedbackless 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 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 6). 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 7). Interestingly,

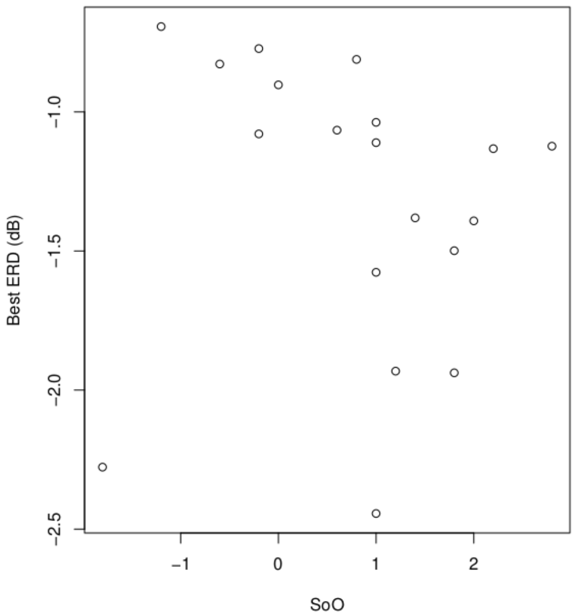

Figure 6: Relationship between the SoO and the ERD in (Škola et al., 2019) (*Embodied* group). Apart from an outlying participant, the higher SoO was bound to the stronger ERD.

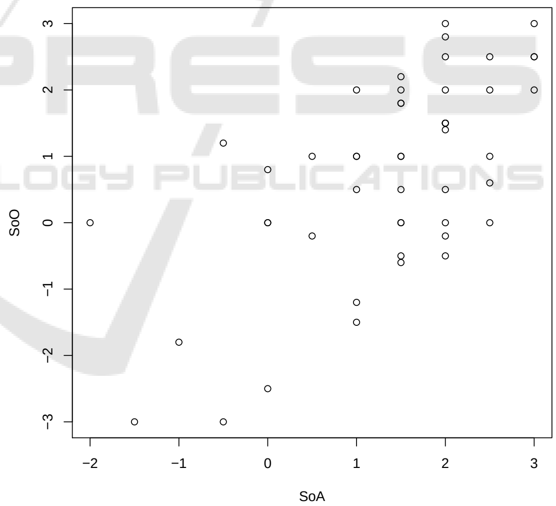

Figure 7: Scatterplot showing the relationship between the reported SoO and the reported SoA (Spearman r = 0.581, p = 0.000, N = 49). Participants tended to experience a high ownership towards the virtual hands controlled by the MI-BCI when the notion of control was also high, indicating sense of embodiment towards the virtual avatar.

the SoA and the BCI performance were not correlated (r = 0.064, p = 0.660, N = 49), see details on Figure 8.

Finally, correlation between the SoO and the online performance was not found (the correlation coefficient was with r = 0.018, p = 0.901, N = 49; see Figure 9).

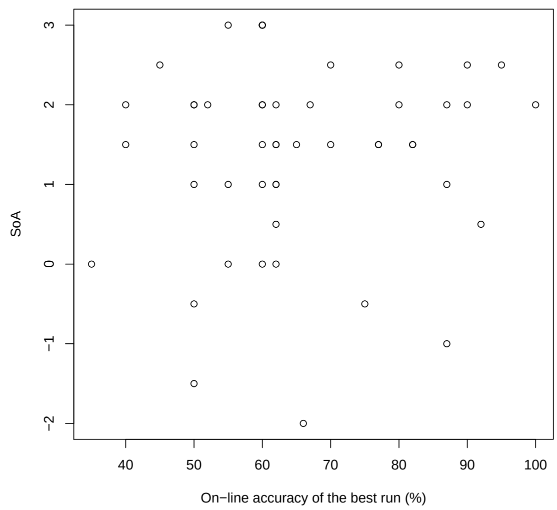

Figure 8: Relationship between the SoA and the actual control proficiency (on-line accuracy of the best run). As the hand movements of the avatar correlated to the participant intentions in case of a good BCI performance (and participants were aware of this fact), correlation between the BCI performance and the SoA (as the self-report on the perceived performance) was expected. However, this was not confirmed.

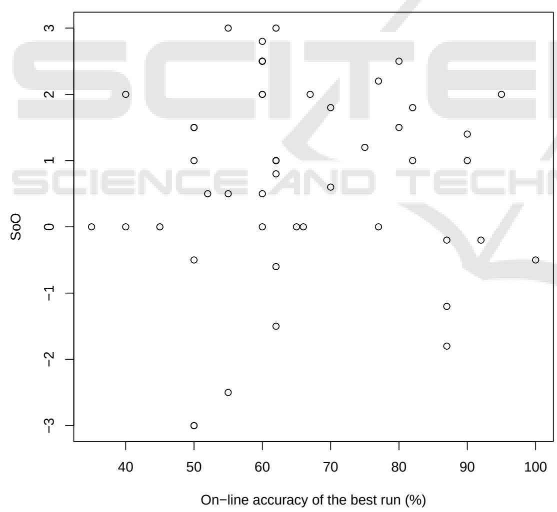

Figure 9: The on-line BCI performance (accuracy) was not related to the perceived SoO in the session.

5 DISCUSSION

Originally, we expected to see a linear relationship between the SoO and on-line BCI performance. 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 his/her 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.

Instead, the SoO was bound together with the SoA. Importantly, 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). It is thus beneficial that the level of the SoO did not rely as much on the performance as it did on the subjectively perceived performance; i.e., the perceived SoA towards the BCI actions (see Figure 7). Thanks to this relationship, the BCI-mediated embodiment arose 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 (Barbero and Grosse-Wentrup, 2010; Faller et al., 2012). Usage of embodiment seems to help participants in tackling the difficulties of the first training stages with a similar mechanism.

Whether the gap between the actual and the perceived performance gets eventually smaller and the users naturally sharpen their skills in self-assessment based on the feedback mapped onto the VR body, or not, needs to be studied in a longitudinal study. It is a question closely related to why the SoA was uncorrelated to the actual performance (accuracy). It is possible that the interpersonal differences in the locus of control and the self-discipline had major influence to the perceived SoA. These effects can be even more pronounced when only a single exposure to the BCI system is made, and the self-assessment would improve after repeated exposure (when comparison with past performances can be done).

Finally, 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 requests 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.

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 embodied feedback.

Providing a 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 the target user group, currently composed of people with paralysis or disabilities. Embodied MI-BCI training in VR could help the users similarly to the VR-based BCI-assisted rehabilitation – by helping to reconnect with the bodily 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 performance. 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 overcome due to the technological advances accompanying the popularization of VR technology. 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 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, for many practical reasons. 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 can easily incorporate the existing body of the user. In the BCI-mediated communication, where users are typically not moving at all, avatar in AR makes perfect sense.

ACKNOWLEDGMENTS

This research was partially supported by the project that has received funding from the European Union's Horizon 2020 Research and Innovation Programme under Grant Agreement No 739578 and the Government of the Republic of Cyprus through the Deputy Ministry of Research, Innovation and Digital Policy.

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