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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 training effort is invested, 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) 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 accuracy for BCI actions (58.3%) than the control group trained with a standard MI-BCI training protocol (52.9%).

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

Current research has very little 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 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 adapts to 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 sufficiently distinct neural patterns on the brain level, the algorithms cannot efficiently extract their intents [7]. Although the

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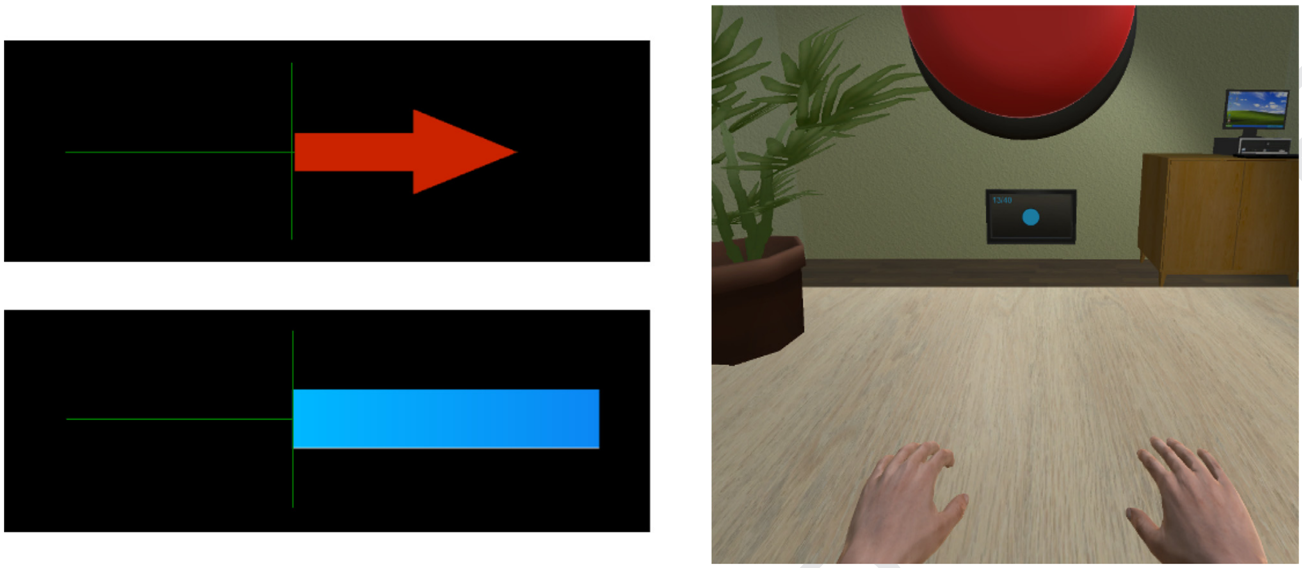

Fig. 1. Comparison of MI-BCI training environments. Left top – example of the Graz training paradigm with symbolic instructions (indicating the user should perform right hand MI), left bottom – feedback in Graz training (indicating detected right hand MI). Right – our embodied VR training environment.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

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 future users to consciously replay 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 Fig. 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 transferred to 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 Fig. 1, right).

There are more benefits in transferring the training process into VR. According to Slater et al. [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 [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. [13] studied an embodied neurofeedback using a human-like hand model 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 was 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 were based on the past literature [13–16], 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. [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

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