MindTrain: How to Train your Mind with Interactive Technologies

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ABSTRACT

Technological products for training the mind that support subjective well-being are gaining popularity in our daily lives. Using Electroencephalographic (EEG) signals for neurofeedback is helpful for learning and a promising approach to train the mind. We introduce MindTrain, a novel, gamified neurofeedback training environment that allows users to learn the skill to voluntarily self-regulate their brain activity in Virtual Reality (VR). MindTrain combines the concept of implicit control with a mobile consumer EEG-wearable in an interactive and immersive VR-environment for visualising the feedback. We tested the feasibility of MindTrain for training to control states of *relaxation* and *concentration*. Our results prove that MindTrain is a promising novel method that warrants further investigation within a larger study. Furthermore, the use of the mobile EEG-wearable demonstrates the potential for bringing MindTrain out of the laboratory into a real-world context.

KEYWORDS

Electroencephalography, Brain-Computer Interface, Neurofeedback, Implicit Control, Virtual Reality, Gamification, Relaxation, Concentration

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1 INTRODUCTION

Training the brain through meditation techniques and technical products for improving concentration levels in addition to relaxing oneself have been slowly gaining prominence and popularity. Use of phone apps such as *Headspace* [6] and other similar products are proliferating in the consumer space. Learning to self-regulate states of relaxation and concentration plays an important role in preventing or even treating stress and exhaustion for therapy as well as subjective well-being.

Neurotechnologies such as electroencephalography (EEG) allow to measure reactions from the nervous system, and thus, to gain information about the user's cognitive or emotional states. Using EEG-based Brain-Computer Interfaces (BCIs), feedback about the current neurophysiological state can be provided to the user [2]. In the clinical domain, BCIs are mainly used as assistive technologies to support disabled people [25] and for neurofeedback training (e.g., supporting patients suffering from attention deficit hyperactivity disorder; ADHD; [16]; see [27] for review). Neurofeedback training is an effective strategy in which people can learn to implicitly modulate their brain activity, thereby showing a positive effect on behaviour and cognitive functions [26]. Beside the clinical applications, the introduction of passive BCIs [28] has led to the exploration of new strategies for human-computer interaction (HCI). With the rise of new mobile, user-friendly EEG-wearables, the possible use of BCIs for training mental states via neurofeedback can be explored outside classical laboratory environments. Some

consumer grade EEG headsets like *Muse* [9] and *NeuroSky* [18], already provide techniques for training the mind.
The beginning of the decade saw the introduction of the Virtual Reality (VR) headset *Oculus Rift* [24] and its effect on consumer level hardware grow leaps and bounds. PC connected headsets such as the Rift and Vive to standalone VR headsets such as Oculus Go [23] have penetrated into many homes. VR technologies present a unique opportunity to provide immersive environments that can simulate a variety of experiences and have also found an increasing use in therapy, BCI applications, and neurofeedback [5, 15, 29].

2 RELATED WORK

Mobile apps such as *Headspace* [6] or *Buddhify* [17] use instruction-based guidance methods for mindfulness and meditation training [3, 8]. These apps rely upon the users to follow the given instructions and self-regulate their subjectively evaluated current state of mind without being in a feedback loop. The *Muse* EEG headset that provides a feedback to the user based on recorded brain activity comes with its own meditation app. Simple auditory feedback in the form of natural sounds such as rain and chirping birds are used to signal the user's current mental state.
Other technologies in combination with BCI can be used to increase interactivity. The game *Meyendtris* combines eye-tracking and passive BCI to adapt its difficulty based on the user's current relaxation and concentration [14]. *My Virtual Dream* used BCI in an immersive and collective art environment allowing participants to voluntary influence specific environmental design parameters in a collective manner [12]. *RelaWorld* combined VR with a laboratory grade EEG headset to introduce a neuroadaptive meditation system. In their VR environment the neurofeedback was based on the acquired level of concentration and relaxation by using alpha- and theta-band activity from EEG. They could show that the VR-enriched neurofeedback training improved participants' subjective meditative experiences [10].

Contribution of the Paper

We introduce a novel, gamified neurofeedback training environment that allows the user to learn the skill of voluntarily changing their brain activity. Therefore, we combined passive BCI with a mobile consumer EEG-wearable and VR, to create an interactive and immersive environment. Thus, we explored how the interactive, gamified environment enabled users to train to control their mental states of *relaxation* and *concentration*. Furthermore, the use of the mobile EEG-wearable demonstrates the potential for bringing these applications out of the laboratory into a real world context.

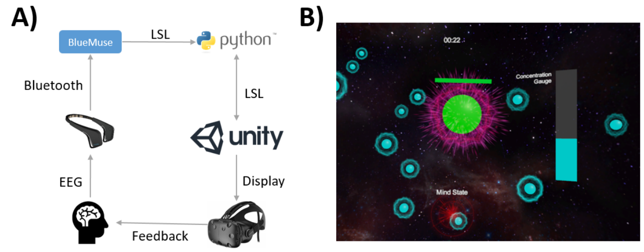

Figure 1: Setup of the application. A) shows the relation between hardware and software components. B) shows the game environment of the MindTrain VR application.

3 SYSTEM OVERVIEW

Figure 1A illustrates our setup comprising the hardware components and software implementations. The hardware consists of the *Muse* EEG headset, the HTC Vive VR headset [4] and a VR capable PC. The software implementation consists of two parts: The VR front-end application for the game built with the Unity Engine, and a back-end with an EEG-based machine learning classifier. The back-end is programmed in Python 2.7 using the open-source BCI Toolbox Wyrm [22] in combination with scikit-learn [19]. For data collection and synchronisation with the VR environment we used the Lab Streaming Layer (LSL; [11]) and the BlueMuse application [13].

VR Front End Implementation

The VR front end consists of two parts: a) the calibration scenario and b) the game scenario (see Figure 1B). The calibration scenario is needed in order to train a machine learning model that can be later used in the game scenario to provide real-time feedback based on the recorded brain activity.

a) Calibration Scenario. A classifier is calibrated in this phase for two mental states: relaxation and concentration. A calibration run consisted of four phases as indicated in Figure 2A. In the relaxation phase, the task for the participant is to first focus on a cross-hair presented in the middle of a virtual dark room with the explicit instruction to relax.
After 10 seconds, the concentration phase starts: A circle is shown to the participant that is changing colours with a frequency of 4 Hz. The participant is asked to count the number of times the circle turns to the colour *yellow*. This is done in order to ensure the participant is in a state of concentration. Afterwards, the number is to be told out aloud by the participant and the correct number appears on the screen as a feedback.

b) Game Scenario. The game scenario also contains of two corresponding phases for the mental states: relaxation and concentration (see Figure 2B). In the relaxation phase, the

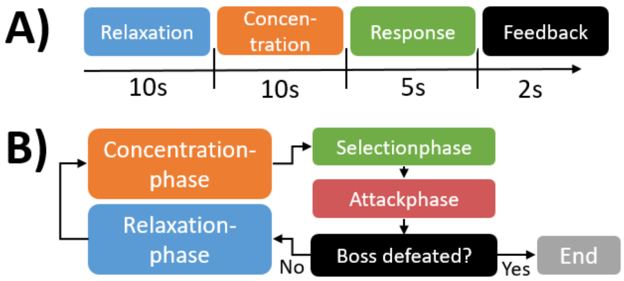

Figure 2: The process flow for the two application phases. A) describes the calibration phase flow. B) shows the game phase flow.

participant is placed in a virtual space with a stationary large purple sphere in front. The main objective of the game is to destroy this large sphere named *Boss*. There are several small spheres of a uniform colour, chosen at random, that are moving around following random paths. The participant is instructed to relax, thereby effecting the speed of the moving spheres. When the participant succeeds in reaching a state of relaxation, the speed of the spheres decreases progressively to a standstill. This approach was achieved by coupling the classifier output to the speed of the spheres. As a reward for successful achievement and maintenance of a certain rate of relaxation, the participant reaches the next game phase. In case of failure, the speed of the spheres increases again as an implicit punishment.

In the concentration phase, the *Boss* starts pulsating in random colours similar to the concentration task during calibration. First, participants have to note the current colour of the small spheres that are standing still. Then they are asked to count the number of times the *Boss* turns to the respective colour as a concentration exercise. After 10 seconds, a beam appears to be shooting from the eye level and set to the orientation of the VR headset. This beam can be used to select multiple small spheres by pointing at them. The participant is asked to select as many spheres as counted. The discrepancy in selected spheres and actual frequency of the large sphere's colour is used to calculate the damage that can be caused. The participant can then shoot the collected small spheres towards the *Boss* by pointing at it through the beam. The consistency of the user staying in concentration state according to the classifier is proportional to the number of actual shots. The participant is penalised by decreasing the number of shots or not providing any shots at all if the consistency of concentration is not maintained. The game ends when the *Boss* is destroyed.

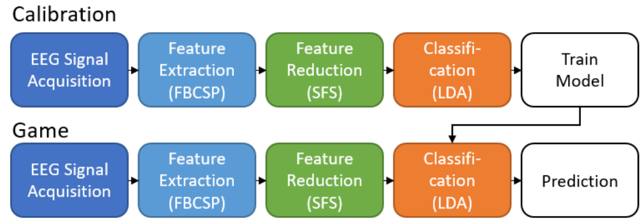

Figure 3: The flow chart shows the process of EEG data acquisition, analysis, and relationship between the calibration and game phases.

EEG Back end

A supervised classifier based on Linear Discriminant Analysis [21] is used for the discrimination of relaxation and concentration (see Figure 3). Filter Bank Common Spatial Pattern (FBCSP) [1] is used to extract features from the data in frequency bands known to correlate with concentration and relaxation: the theta band (4-8 Hz) and the alpha band (8-13 Hz) of the frontal electrodes [5, 10]. Concentrating on these frequency bands also avoids the possible influences of muscular activity in the EEG signals, which are usually above 30 Hz [7]. Afterwards a Sequential Forward Selection (SFS) procedure [20] is used for dimensional reduction of the feature space.

For the data in the calibration phase, 10 second blocks from the concentration and relaxation phases are grouped separately. Each of these is split into non-overlapping 5 second time windows that is then fed to the FBCSP. However, for online classification during the gameplay we use a ring buffer with a time window of 5 seconds of EEG data and a sliding window of 1 second similar to [14]. The classifier provides real-time prediction of the participant's mental states during the main game. The probability prediction for each mental state affects speed of the small spheres in the relaxation phase and the number of shots in the concentration phase. In the relaxation phase, participants are rewarded if they have relaxation classifier probability of more than 0.5, by decreasing the speed of the small spheres, else penalised by increasing it proportionally to the actual probability. Similarly, in the concentration phase, the participants are penalised by reducing the number of shots or rewarded by increasing the number of shots proportional to the classifier output.

4 EVALUATION PROCEDURE

To evaluate the MindTrain system, participants were invited for a pilot study. Four participants took part in the study (two males, two females) with an age ranging between 19 and 34 (*M*= 25, *SD*= 6.48). Three of them had experienced VR applications before while two were familiar with EEG.

Part.	PPV	NPV	ACC
1	0.87	0.72	0.78
2	0.78	0.8	0.79
3	0.73	0.73	0.72
4	0.69	0.68	0.69
Mean	0.77	0.73	0.75

Table 1: The positive prediction value (PPV, precision), negative prediction value (NPV), and classification accuracy (ACC) from the calibration where the relaxation state is positive and the concentration state is negative.

To quantify the skill of voluntarily changing their brain activity we measured the time participants needed to bring the small spheres to a standstill during the relaxation phase which is based on the classifier output. In addition, number of runs they required to defeat the *Boss* is also recorded. Furthermore, the probability output of the classifier during the relaxation and concentration phases was calculated in the main game. During the study, participants sat comfortably on a chair in a quiet room. The *Muse* headset was first placed on the participant's head followed by the VR headset and checked for good signal quality. After the calibration, the participant was given a trial run for the main game with the experimenter simulating the output of the classifier. To gather training data for the classifier, each participant went through 20 calibration runs in total. The game scenario was then started with the online-classification till the *Boss* was destroyed. During both the calibration and game sessions the participants were instructed to perform no movements to minimise the influence of muscular activity.

5 RESULTS

The calibration model for each user was verified to test the quality of the trained model using stratified K-fold cross-validation with a fold value of 5 with the classification results shown in Table 1.

Figure 4A shows the mean value of the time needed to have the small spheres come to a standstill across all relaxation phases per participant. The mean value across all participants was *M*= 26.4 seconds (*SD*= 10.01). The results indicate that those participants that needed a longer time to reach the state of relaxation, were not able to maintain it steadily.

Figure 4A also shows the number of runs needed to complete the game per participant. This number was related to their performance during the concentration phase of the gameplay.

Interestingly, Figure 4B shows that participants who on average needed more runs showed a decreasing trend of time

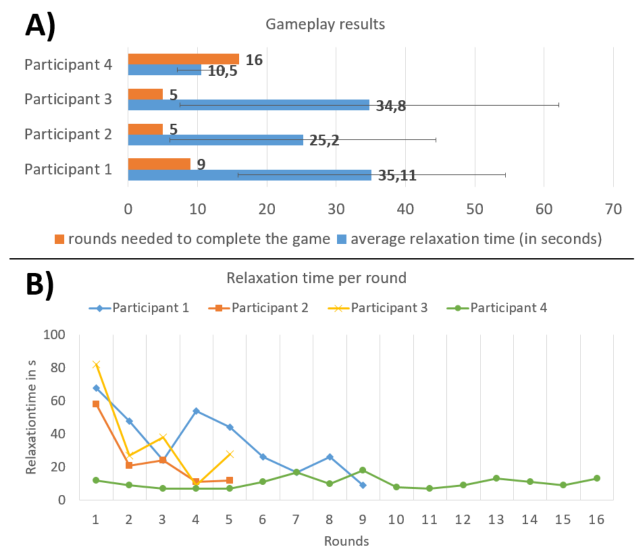

Figure 4: Gameplay results. Graph A) shows both the average time the user needed to complete the task in the relaxation phase and the number of runs to complete the game. Graph B) shows the relaxation time over the runs.

needed to bring the small spheres to standstill with each consecutive run.

6 CONCLUSION AND FUTURE WORK

In this work we introduced a novel, gamified neurofeedback environment in which we combined a passive BCI approach with VR and a mobile consumer EEG-wearable. We found that the EEG-wearable showed a good performance for such applications. Interestingly, participants exhibited different abilities to either modulate their brain activity during the relaxation phase or to stay concentrated in the pilot study. It seems that there is a trade-off between being good at concentrating compared to coming down to a relaxation state. Thus, our system allows participants to train themselves to control their states of relaxation and concentration. The feedback from the participants in the pilot study and the results are encouraging to show the effectiveness of our system.

Our pilot study also laid a foundation for possible future improvements and research. We plan to modify the game mechanics in the next version and couple the strength of ammunition to the classifier output. Furthermore, we foresee a level based game scenario, where the difficulty scales with the participant's performance over time. Lastly, we will also research into other possible calibration tasks for the collection of training data that might further optimise the game mechanics. In addition, studies on a larger scale are necessary to study the utility of our novel method for training the mind.

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