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EEG-BASED STIMULUS CLASSIFICATION IN A FULL-BODY MOVEMENT, VIRTUAL REALITY PARADIGM

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ABSTRACT: The use of EEG brain-computer interfaces (BCI) during movement is inherently difficult due to motion artifacts interfering with measured brain signals. Thus, most BCI research utilizes rather immobile conditions, thereby decidedly limiting its range of use cases. We aim to overcome this restriction by introducing a novel virtual reality paradigm which allows full-body movement of participants in combination with a processing pipeline specifically designed to deal with motion artifacts. Stimulus discrimination (target versus distractor) upon fixation was tested in 32 participants. Results indicate that targets elicit a higher P300 amplitude than distractors. Comparing the performance of different classifiers, shrinkage linear discriminant analysis (sLDA), support vector machine (SVM), and EEGNet, yielded equally sized, above chance classification accuracies. Overall, the results suggest the feasibility of studying and applying BCI in full-body motion paradigms given refined data preprocessing. The authors conclude with suggestions for future BCI studies in motion.

INTRODUCTION

After the first years of brain-computer interface (BCI) research, during which BCI was mainly investigated as a means to partially compensate lost motor functions in people with severe motor disabilities, research on applications of BCI expanded to its use in non-medical areas. Following Zander and Kothe [1], BCI will be most beneficial to a wide range of applications if it does not replace or compete with fundamental human interaction patterns, like using hands or speech. Rather, it should substantially add value to the human-computer interaction (HCI) without distracting the user in his/her task. Because this kind of BCI covertly, or rather *passively* boosts HCI, it's referred to as passive BCI (pBCI) which will be the object of this paper.

Promising fields for BCI usage beyond medical application are summarized by van Erp, Lotte, and Tangermann [2] as device control, user state monitoring, evaluation, training and education, gaming and entertainment, cognitive improvement, as well as safety and security.

Even though, there is a definite vision to apply pBCI in real-life contexts, most of the research has been conducted in highly controlled laboratory settings which are limited in their ecological validity. A major challenge in investigating pBCI under highly realistic (simulated) or real scenarios lies in their inherent complexity comprised of artefacts, non-brain influences, and other mental states [3]. Some research has been done to fill this gap and promising results were obtained, yet most studies were conducted in seated scenarios, notably driving, aviation, and desktop gaming. Of all studies included in the review [3], only one investigated participants who were standing and moving rather freely while performing a surgical task [4]. We believe it is imperative to conduct more studies allowing for free full-body movement in order to make pBCI applicable universally in real-life scenarios and not only in seated conditions. To achieve this goal, we introduce a new paradigm which allows participants to move and interact freely in a relatively fast-paced game-like scenario. First promising results of electroencephalography (EEG) analysis will be presented underlining the feasibility to work with pBCIs in a rather movement-intensive environment.

To deal with motion artifacts, we adopted methods from another discipline which has emerged to understand brain and body in motion: Mobile Brain-Body Imaging (MoBI; [5]). For MoBI studies, it's common to apply joint measurements of EEG, muscular activity, motion capture, and eye tracking. This, in combination with elaborate data processing techniques, like independent component analysis (ICA) for artifact rejection or machine learning for pattern recognition, proved to be efficacious in studying EEG in moving participants [6,7]. We combined MoBI with virtual reality (VR), an emerging tool to investigate more realistic scenarios, permitting participants to move around freely, while at the same time being highly controllable [8].

To demonstrate the feasibility of our setup, we investigated two well-established findings of BCI research. First, we aimed at replicating the P300 response and second, we compared the most common BCI classification algorithms in terms of their performance in a visual categorization task. In both cases we investigated fixation-related potentials (FRP), i.e. the cortical patterns locked to the onset of a fixation.

Replicating the P300 component: The main goal of this first step is a proof of concept: investigating whether we can replicate a typical pattern of cortical activation, the P300 in response to targets vs. distractors, in such a movement-rich paradigm.

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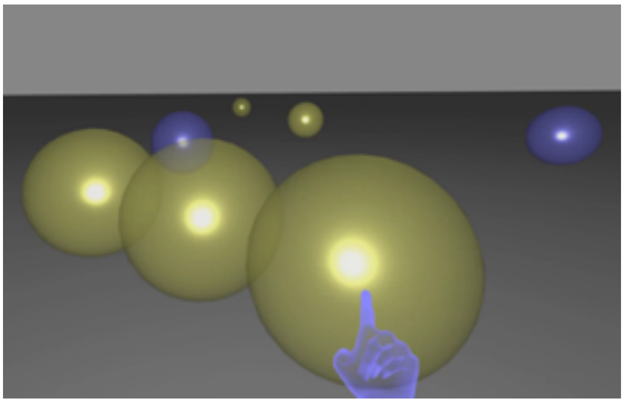

Figure 1: Stimulus presentation in virtual reality. Spheres flow towards the participant. The translucent blue hand represents positioning of the controller and bursts spheres upon touch. Depicted is a condition in which sphere color is permanently visible and colors are easy to distinguish.

While the P300 speller is probably the most popular application of this cortical potential in a BCI (first demonstrated by Farwell and Donchin, [9]), there are numerous examples of BCI studies investigating the P300 [10]. De Vos, Gandras, and Debener [11] investigated the P300 on walking participants while they performed an auditory oddball task. They were not only able to replicate the P300 component to rare targets, also single-trial classification in the P300 time window worked with a decent accuracy of 64%.
In our experiment, P300 was analyzed to visually presented targets and distractors. Since stimuli were appearing in a rather fast paced, free-viewing environment, some challenges had to be addressed to obtain a meaningful FRPs (for a detailed discussion of free-viewing paradigms see [12]). First, fixation durations were shorter than the following cognitive processes: a fixation usually lasts around 200-300ms [13], but some cognitive components, like P300, occur even later. Hence, components to subsequent fixations would overlap. This overlap can be controlled for mathematically with a linear regression [14,15]; which also deals with non-uniformly distributed artifacts caused by eye movements systematically affecting FRP averaging [16]. Thus, we chose to "detangle" FRPs in a regression-based approach. In the first part, we focused on the cortical activation to targets versus distractors in a time window of 200-600ms. It was hypothesized that amplitudes to targets will be larger than to distractors.

Comparing classifiers for visual categorization: Next, cortical activation to targets and distractors was classified with different algorithms in order to demonstrate the feasibility of EEG classification in such a motion-intensive VR task. Therefore, we compared the performance of the three most popular classifiers in BCI research as reviewed by Värbu, Muhammad, and Muhammad [17]: linear discriminant analysis (LDA), support vector machines (SVM) and convolutional neural networks. We investigated the standard LDA as well as shrinkage LDA (sLDA) and we worked with EEGNet as neural network. LDA and sLDA both aim to find a linear combination of features that most effectively separates two or more classes, with sLDA being less prone to overfitting [18]. SVMs find hyperplanes to maximize margins between different classes [19]. Lastly, EEGNet is a specialized compact convolutional neural network architecture tailored for the interpretation and analysis of EEG signals, designed to offer both high interpretability and robust performance in BCI tasks [20]. EEGNet performs feature extraction autonomously based on the data, whereas for LDA and SVM features must be extracted in a separate step.
For all methods, we hypothesize that the validation accuracy will be significantly above chance. Further, we expect the best classification performance for EEGNet, as it is specifically designed to classify EEG signals. Due to overfitting issues, LDA might work least accurately.

MATERIALS AND METHODS

Participants: 48 participants were invited to the study and met the inclusion criteria: good health, sobriety, right-handedness, no preexisting neurological issues, normal or corrected-to-normal vision. During the experiment, 16 participants were excluded due to inaccurate eye-tracking (7), technical issues (6), motion sickness (1), pain from EEG cap (1), or below chance performance in the task (1). In total 32 participants (age 22-45, $\bar{x}$ = 28.81 ± 5.00 years, 19 female) finished the experiment and were included into analysis.

Study design and procedure: After giving informed consent, participants answered demographic questions and were set up with an EEG. They then performed a workload calibration task which will be part of another analysis. The main object selection task was performed in a visually sparse VR environment created in Unity 3D. It consisted of a grey floor and sky with the controller represented by a translucent blue hand. In the experiment, spheres with a diameter of 0.5 m spawned with an angle of ± 50° left or right in front of the participants. Spheres were colored either bright blue or yellow, grayish blue or yellow, or in isoluminant gray. Spheres floated towards the participant where they disappeared either because the participant touched a sphere, or it reached the center of the virtual world. Upon destruction, three different sounds were played depending on whether the destruction was a hit, false alarm, or a miss. No sound was played for a correct rejection. Color, speed and spawn distance of the spheres depended on the condition. A 2x2x2 repeated measurements design resulted in varying difficulty levels with the factors: distinguishability (color was easy or hard to distinguish), predictability (constant or random inter-stimulus intervals), and visibility (color visible permanently or upon fixation). During 4 training blocks, participants got accustomed to the conditions. In the main part, all 8 conditions were presented in pseudo-random order, split into 2 blocks each, while the target/distractor color was counter-balanced over all participants. Each block contained 240 spheres (120 targets) and lasted 180s. After each block NASA-TLX [21] and 3D-SART [22] were collected for a separate analysis. In total, the

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experiment lasted for 3.5-4.5 hours per participant, including breaks.

Instruments: For workload calibration a 27" HD monitor was used. The main experiment was conducted using a head-mounted display (HMD, HTC Vive) and an HTC VR controller. Positions of HMD and controller were tracked with the SteamVR Lighthouse tracking system. The HMD additionally had an inbuilt eye tracking system by SensoMotoric Instruments. Both motion and eye tracking data was streamed with a sampling rate of 90 Hz using Lab Streaming Layer (LSL, [23]). Events such as block starts and ends, sphere spawns and destructions, and eye gaze fixations were recorded in LSL. EEG was recorded using a 128-channel ANT eego sports system with passive Ag/AgCl electrodes and active cable shielding (ANT Neuro, Hengelo, Netherlands) with a backpack-worn tablet PC streaming the data wirelessly to LSL. To our knowledge, no high pass filter was applied during recording. The EEG was referenced to the vertex electrode, grounded with an electrode at the ear lobe and recorded with a 500 Hz sampling rate. Impedances were below 20 kΩ.

EEG preprocessing: Preprocessing of the EEG data was done in EEGLAB [24] in MATLAB using the BeMoBIL Pipeline with minor adaptations [25]. Taken together, preprocessing consisted of three steps: (1) Data import and synchronization of the different streams. (2) Data downsampling to 250 Hz, line noise removal using Zapline-plus [26], detection and interpolation of bad channels using the *clean_rawdata* EEGLAB function, and referencing to the average. (3) Artifact removal using the adaptive mixture independent component analysis (AMICA; [27]), rejecting all non-brain components as determined by the ICLabel toolbox [28].

Calculating fixation-related potentials with the Unfold toolbox: To prepare for further analysis, the cleaned EEG data was filtered with a low pass filter of 35 Hz and a high pass filter of 0.2 Hz passband edges, respectively. To deconvolve overlapping EEG signals and to model the influence of artifacts the Unfold toolbox for MATLAB was used [29]. The Unfold toolbox was designed to recover isolated neuronal responses from originally overlapping cortical signals by reconstructing the deconvoluted signal mathematically. For every event of interest, a regression model is defined which is then fitted to each time point and channel relative to the onset of an event. The following events were supposed to influence the phenomenon of interest and were therefore included as a regression model: last fixation onset, fixation onset, final fixation exit, sphere spawn, sphere destruction, and sphere collision. For a more detailed description of the process including regression equations, see Rabe [30]. The Unfold toolbox returns beta weights which we then used to reconstruct the deconvoluted FRPs by summing up grand mean, regression weights of main effects, and interaction terms.

The following data was included into further analysis: (1) only trials in which participants correctly reacted to targets (hit) or distractors (correct rejection), (2) only last fixations on a sphere, i.e. before an action was performed on it (hit a target) or not (dismiss a distractor), (3) activation from -1 to 2 ms around the fixation event (750 timepoints), (4) only Pz electrode because the most elevated P3 amplitudes can be expected over the centroparietal cortex [31]. Paired t-tests comparing target amplitudes against distractor amplitudes were conducted for each timepoint. Peak amplitudes to targets and distractors were averaged +/- 10 ms around the peak in a time window of 200-600 ms. Then, a one-sided t-test (hit>distractor) was conducted. Normal distribution was assessed visually with QQ-plots and could be assumed.

Classifying on target and distractors: Classification was performed on the preprocessed but not unfolded dataset. All input time intervals were locked to fixation onset. In order to exclude brain responses related to motor execution we only included fixations on spheres that were more than 4 meters away (head to sphere distance), i.e. out of reach for the participant.

For classification, four algorithms were applied: LDA, sLDA, SVM, and EEGNet. Features needed to be extracted as input for LDA, sLDA, and SVM while EEGNet is designed to detect features automatically, thus it used the preprocessed data directly. Feature extraction will be described in the following.

First, epoching was done with a time window of [-1000 1500] ms and a baseline between [-400 -200] ms. Epoching steps were conducted in EEGLAB and resulted in a three-dimensional data matrix (channel x time x epoch). Second, the timeframe of [0 600] ms was used for feature extraction. This 600 ms period was split into 15 non-overlapping moving windows of 40 ms each. Third, amplitude averages were calculated for each window across all channels and epochs. Lastly, the resulting feature matrix (epoch x 1935) was fed into the classifiers (LDA, sLDA, SVM). To validate the classifiers' performance, 5-fold cross-validation was conducted. Finally, statistical significance levels were calculated with a permutation-based approach, written by Laurens Krol (based on [32]). It generates a synthetic dataset of the same size and randomly shuffles the classes 25,000 times. This produces a distribution of random correct assignments for comparison with our classifications. For $\alpha = 0.01$, significance is reached with 53.06% accuracy.

MATLAB R2021a and the EEGLAB 2022.1 toolbox were used for preprocessing. The SVM model used a linear kernel and a box constraint value of 0.01 to prevent overfitting. The LDA, sLDA and EEGNet models were developed using Python 3.8.8. For EEGNet, Keras (v3.0) was used. The software components were executed on a system equipped with the following hardware specifications: an AMD Ryzen 5 3600X 6-core processor running at a clock frequency of 3.80 GHz, 16 GB of RAM.

RESULTS

P300 to targets and distractors: Our hypothesis was that amplitudes of the FRPs in a time window of 200-600 ms on Pz electrode would be larger to targets (i.e. hits)

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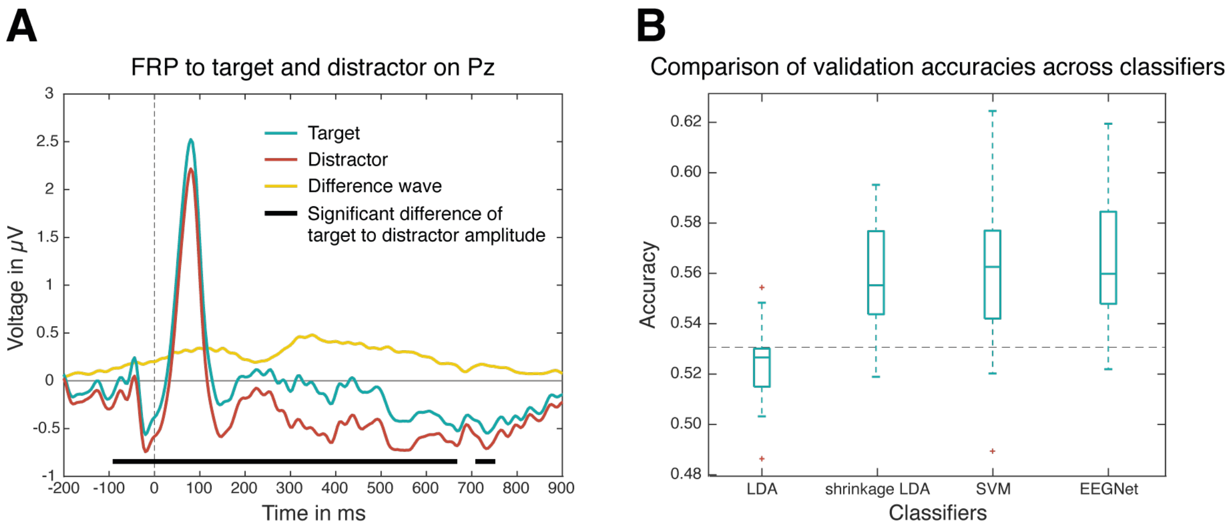

Figure 2: (A) Fixation-related potentials (FRP) to last fixation onset, 0 ms, on target or distractor. Significant differences in amplitude are indicated (pairwise t-test per timepoint, p<0.05) (B) Performance of different classifiers for classification of brain activation to targets or distractors. Each boxplot indicates the spread of accuracy percentages. Statistical significance level of above chance performance is indicated with a horizontal dashed line at 53.06%.

than to distractors (i.e. correct rejections). T-tests of the amplitudes on every single timepoint against each other revealed a significant difference with $p < 0.05$ for most timepoints between around -100 ms to 750 ms (timepoints marked in Fig. 2). Comparison of the peak amplitudes indicated that during the 200-600 ms period after fixation onset, the average peak amplitude for targets was 1.05 µV ($SD = 0.96$), while for distractors it was 0.79 µV ($SD = 0.95$), showing that targets had a peak amplitude that was, on average, 0.26 µV higher than that of distractors ($SD = 0.47$). A paired one-sided t-test comparing the peak amplitudes (targets > distractors) confirmed a significant difference ($t(31) = 3.12, p < 0.01, d = 0.55$).

Classifier performances: For the evaluation of EEG data classification, four algorithms—LDA, shrinkage LDA, SVM, and EEGNet—were assessed using 5-fold cross-validation. Fig. 2 demonstrates the distribution of the validation accuracies. On average, 2307 valid epochs were included for each participant, with an almost balanced ratio of targets to distractors. We hypothesized classification accuracies above chance for each method, with EEGNet performing best and LDA performing worst. Results show that all classifiers except LDA ($\tilde{x}$ = 52.7%) performed above random - sLDA $\tilde{x}$ = 55.5%, SVM $\tilde{x}$ = 56.3%, and EEGNet $\tilde{x}$ = 56.0% -, i.e. median values exceeding the estimated threshold of 53.06 %. All classification accuracies for training and validation can be seen in Tab. 1.

DISCUSSION

In this study, participants had to react to floating spheres of two colors in a VR environment. While the spheres were approaching towards the participants, they had to touch targets and dismiss distractors. We were interested in the cognitive reaction to targets and distractors upon fixation and the possibility of a fixation-based BCI. Our analysis was split into two parts: (1) comparing FRP amplitudes upon last fixation onset to correctly identified targets (hits) and distractors (correct rejections), (2) assessing the performance of different classifiers (LDA, sLDA, SVM, EEGNet) to distinguish between targets and distractors. For the first part, the amplitudes in a P300 time window were larger for targets than for distractors, both during peaks and at each time point. In the second part, above chance classification accuracies were achieved for all classifiers but LDA. Performance of SVM, sLDA, and EEGNet was almost equal.

Cortical activation around fixation: Since the participants were in full-body motion during the experiment, we investigated whether it was generally possible to replicate a well-studied cortical response in our paradigm despite movement artifacts. The P300 was analyzed because it has been repeatedly shown to be a discriminator between targets and distractors [33–37]. Our analysis confirmed the hypotheses: during the P300 time window, FRP amplitudes to targets were higher than to distractors, both for the peak and for each timepoint. Unexpectedly, this difference emerged already 100ms before stimulus fixation which was not reported by other free-viewing studies [33,34,36]. The sustained elevation of amplitude to targets compared to distractors from -100 ms to 750 ms around fixation onset may stem from parafoveal processing before fixation onset, potentially present in all blocks where color visibility was constant

Table 1: Median training and 5-fold validation accuracies for the different classifiers

Classifier	Training	Validation
LDA	92.9%	52.7%
sLDA	71.8%	55.5%
SVM	68.8%	56.3%
EEGNet	60.1%	56.0%

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(half of the trials). Such modulations might have affected the overall FRPs calculations. Indeed, early modulations of amplitudes can be seen in free-viewing tasks, and not in replay or oddball tasks [35]. Another possibility is that participants already distinguished between stimuli during earlier fixations. Unlike in the *last* fixation (which we investigated), a person is likely to decide during the *initial* fixation whether a stimulus requires further attention. This might influence the cortical activation to that same stimulus during following fixations. Supporting this idea, another study showed FRP modulations for repeated object fixation [38].

The prominent spike at approximately 40-120 ms post fixation onset most likely reflects a visually evoked lambda response, a potential unique to free-viewing studies and originating from the striate or extrastriate cortex [12].

Overall, and most importantly, we could demonstrate a substantial difference in amplitude to targets compared to distractors after stimulus fixation even in a paradigm with full-body movement and fast-paced events. This serves as a first proof of concept for the feasibility of analyzing brain responses in our novel VR interaction paradigm. Further investigations should address the potential influence of parafoveal stimulus discrimination and repeated stimulus fixation to improve understanding of cortical responses in free-viewing paradigms and to pave the way for EEG analysis in more realistic research scenarios.

Classifying stimulus discrimination: In an online classification of neuronal processes, it might be of interest to identify whether a participant is evaluating a stimulus as target or as non-target, for example to indicate whether the participant intents to interact with that stimulus. As a first step towards that goal, we compared the performance of four different classifiers, offline, to predict target and distractor discrimination from brain activation after fixating a stimulus. Three of the classifiers, sLDA, SVM, and EEGNet, yielded an above chance accuracy. Only LDA failed to reach that level. Low performance of LDA was predicted before because of its overfitting issues [18]. We expected the best performance of EEGNet, however all classifiers performed equally well with mean validation accuracies between 55.5-60.0%. One reason for the similar outcomes might have been the relatively noisy data, compared to other paradigms. We argue that it may create a ceiling effect in classification accuracy which could be topic of investigation in subsequent analyses.

We identified several factors that, if considered in future analyses, could improve classification accuracies. Probably, the overlap between cortical activation to subsequent stimuli hampered the classifiers' ability to effectively distinguish between targets and distractors. In the first part of our analysis, we showed that by "detangling" overlapping cortical responses with a regression-based calculation we were able to replicate results of studies without this overlap. It is advisable to come up with a similar method that can integrate well with classification to reduce the noise produced by overlapping responses. Further, all EEG channels were used for classification without spatial filtering. Optimization could be achieved by concentrating on more relevant electrode locations. As target and distractor discrimination represented by the P300 is primarily found over the centroparietal cortex [31], we argue that respective electrodes should be elevated by a spatial filter. Finally, motion artifacts might still have obscured some of the brain signals as the paradigm was quite motion-intensive. Since all applications of BCI in motion will face similar issues we suggest the exploration and integration of more sophisticated artifact rejection techniques to ensure cleaner, more reliable data inputs.

CONCLUSION

To the best of our knowledge, this was the first study classifying stimulus discrimination in a 3-dimensional VR environment with high stimulus frequency and full-body motion, investigating more innate interaction patterns than standard 2-dimensional monitor based experiments. The findings indicate that it is feasible to classify cortical activation patterns to stimulus discrimination despite body movements. Our results can be regarded as a promising first step to investigate and apply BCI in motion, making it more accessible for a wide range of human-computer interactions.

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