Using EEG to Decode Subjective Levels of Emotional Arousal during an Immersive VR Roller Coaster Ride

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Abstract

Emotional arousal is a key component of a user's experience in immersive virtual reality (VR). Subjective and highly dynamic in nature, emotional arousal involves the whole body and particularly the brain. However, it has been difficult to relate subjective emotional arousal to an objective, neurophysiological marker—especially in naturalistic settings. We tested the association between continuously changing states of emotional arousal and oscillatory power in the brain during a VR roller coaster experience. We used novel spatial filtering approaches to predict self-reported emotional arousal from the electroencephalogram (EEG) signal of 38 participants. Periods of high vs. low emotional arousal could be classified with accuracies significantly above chance level. Our results are consistent with prior findings regarding emotional arousal in less naturalistic settings. We demonstrate a new approach to decode states of subjective emotional arousal from continuous EEG data in an immersive VR experience.

Index Terms: Human-centered computing—Human computer interaction (HCI)—HCI design and evaluation methods—Laboratory experiments; Applied computing—Life and medical sciences—Consumer health

1 Introduction

VR technologies allow to create highly immersive and contextually rich scenarios. Their involving nature can evoke strong emotions in the user of the VR system [4]. It is therefore of interest for developers and operators of VR applications to keep track of the user's continuously and individually fluctuating emotional states to ensure the intended quality of the VR experience and the user's well-being. Objective measures that correlate with subjective emotional experience could be used to monitor the current (affective) state of the VR user without interfering with her immersion into the virtual environment. Emotional arousal—a key component of subjective emotional experience [10]—has recently been associated with changes in EEG-derived alpha oscillations (8-12 Hz) in parietal cortex areas [7]. Here we examined whether alpha power can be used to distinguish states of high and low emotional arousal using continuous EEG signals acquired during an immersive VR experience.

2 Experimental Setup

38 healthy participants (20 females, age range 18–35) experienced a 280 s VR episode, consisting of two virtual roller coaster rides (153 s and 97 s), separated by a 30 s break. The episodes were commercially available [5] and presented on an HTC Vive head-mounted display (HMD) while simultaneous EEG activity was recorded. To avoid signal disturbances, participants were instructed to keep their head in a steady position, looking straight.
Then a playback of the recorded experience was presented on a virtual 2D screen in the HMD. The replay served as a memory aid for participants to remember how emotionally aroused they felt in each single moment of the experience. A vertical rating bar displayed next to the video allowed them to continuously report the recalled level of emotional arousal by using a probe dial (Griffin PowerMate).

2.1 EEG measurements

30 channels of EEG activity were recorded in accordance with the international 10/20-system using a mobile amplifier (*LiveAmp*) and active electrodes (*actiCap*; both by BrainProducts, Germany). Two additional channels of electrooculogram (EOG) allowed keeping track of eye movements. Data were sampled with 500 Hz and referenced to electrode *FCz*. The HMD was placed carefully on top of the EEG cap before impedances were brought below 10 kΩ.

2.2 Data Analysis

To exclude effects related to the on- or offset of the roller coasters, the first and the last 2.5 s were removed from all data streams recorded during the two roller coaster episodes. Combining these with the intermediary 30 s break resulted in time series of 270 s length which went into the analyses.

Behavioral arousal ratings Ratings were resampled to 1 Hz by averaging non-overlapping sliding windows, yielding one arousal value per second. To achieve distinct classes of arousal ratings (low, medium, high) per participant, the set of all (second by second) ratings in a given data set was divided into three equally sized subsets by applying a tertile split.

EEG preprocessing EEG data were preprocessed and analyzed with custom MATLAB scripts building on EEGLAB toolbox (v13.4.4b) [3]. Data were downsampled to 250 Hz and PREP pipeline (v0.55.2) [1] default procedures were applied for high-pass filtering (1 Hz, FIR filter), line-noise removal (50 Hz), robust referencing to average, and detection as well as interpolation of noisy channels. Subsequently, EOG activity was subtracted from the EEG signal with a regression based approach [9]. To exclude artifact contaminated segments of the data, we applied an automatized rejection criterion based on extraordinary bursts of variance in the signal.

Dimensionality reduction We used spatio-spectral decomposition (SSD) [8] and respective spatial filtering to extract 15 components with maximal signal-to-noise ratio. To test our main hypothesis that frequencies in the central alpha range allow the discrimination between different states of arousal, we applied SSD with the signal defined as the frequency band 10±2 Hz and the noise bands as the neighboring spectra (6±1 Hz and 14±1 Hz). As a control and to assess how much other frequency bands contribute to the classification, we applied the same approach over a broad array of potential

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2018 IEEE Conference on Virtual Reality and 3D User Interfaces
18-22 March, Reutlingen, Germany
978-1-5386-3365-6/18/$31.00 ©2018 IEEE

signal frequency bands ($f_s \pm 2$ Hz) surrounding the alpha range ($f_s \in \{6, 8, 12, 14, 16, 18, 20, 22, 24, 28, 32\}$). Data of the extracted components were either kept band-pass filtered around the signal range (*narrow band*) or in a broad frequency range (5 to 35 Hz) in order to allow multiple spectra to contribute to the classification (*broad band*).

Feature extraction Using BCILAB (v1.4-devel) [6], we applied the common spatial patterns (CSP) [2] algorithm to extract band-power based features from the signal. CSP specifies a set of spatial filters to project the EEG data onto components whose band-power maximally relates to the prevalence of one of two distinct states (here: high vs. low emotional arousal). Data were epoched in segments of 980 ms length, allowing a 20 ms window between epochs to eliminate the possibility of overlap. A feature vector with the logarithmized variance of the six most discriminative CSP components (using three filters from each side of the eigenvalue decomposition matrix) was extracted per epoch.

Classification Fisher's linear discriminant analysis (LDA) was used as classifier. Validation and hyperparameter optimization (regularization of covariance matrices) were realized with a nested (5×10), randomized cross-validation. Average classification rate for the epochs of the validation sets of the outer loop was taken as the outcome variable to assess the predictive quality of the model.

Benchmark To compare the classification performance to an empirical baseline, we ran all approaches specified above on a copy of the data set in which individual arousal ratings were replaced by an uncorrelated rating template (sinusoidal curve with a wavelength of 30 s oscillating between high and low arousal).

3 Results

Behavioral rating results and an example of the clustering into classes of high and low arousal are reported in Fig. 1(a-b). The average classification accuracy for the data set that was SSD-augmented and narrow band filtered in the frequency range from 8 to 12 Hz was 63.80% ($SE = 0.99\%$). For the broad band filtered data (augmented in the alpha range), the accuracy was 74.40% ($SE = 1.50\%$). The results for other signal frequencies f_s are depicted in Fig. 1(c). Excluding the break from the analysis did not change the results. Models which were calculated by using the artificial rating template did not perform significantly better than chance level. Fig. 1(c) shows averages of the spatial pattern weights over all participants for two representative frequency bands. If the central alpha band (8-12 Hz) was targeted (blue boxes), the patterns show a strong temporo-parietal component. Patterns for an exemplary higher frequency band (brown boxes) exhibit a ring-shaped topography along the borders of the cap, thus indicating the presence of artifactual EEG components.

4 Conclusion

Our results show that it is possible to predict subjective emotional arousal during a VR experience from brain activity. In particular, we could discriminate periods of high and low emotional arousal with above-chance accuracy using a spatial and spectral decomposition of the EEG signal. In accordance with prior findings [7], an increase in emotional arousal was associated with desynchronization of alpha oscillations in temporo-parietal areas. The prediction accuracy could be further increased when the analysis included or focused on higher frequency ranges, but the corresponding topographies suggested that confounding non-neuronal sources might have driven the classification in these parts of the spectrum. If the aim is to learn about the brain's processing of emotional arousal or to provide an interface that most widely relies on neuronal activity, our results indicate that oscillatory power in the high alpha and low beta range, particularly in temporo-parietal areas, might be the most promising marker.

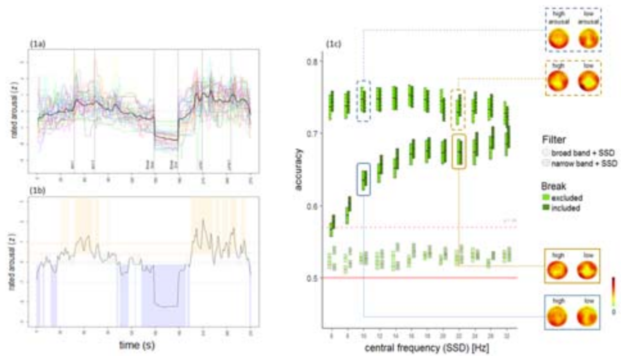

Figure 1: (1a-b) Time series of rating data. (1a) Ratings of all subjects with their average plotted in black. Selected events during the experience are marked by dotted vertical lines. (1b) Exemplary rating from a single participant and clustering into epochs of *high* (orange) and *low arousal* (blue). (1c) Average classification accuracies for narrow and broad band approaches (*mean*±1*SE*). Grayed-out boxes represent the results for models in which the ratings were replaced with an uncorrelated template (uninformed benchmark). Red lines indicate chance level (solid) and 95% confidence interval (dashed). Very right: Average spatial activation patterns (normalized) of the two most discriminative components (SSD+CSP) for models trained on different signal frequencies.

Acknowledgments

Thanks to Mert Akbal, Nicolas Endres, Cade McCall, and Firat Sansal for substantial ground work and their contributions to the experimental paradigm.

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