Neurophysiophenomenology – predicting emotional arousal from brain arousal in a virtual reality roller coaster

Alberto Mariola* [a,c], Felix Klotzsche* [a,b], Simon Hofmann* [b,d], Vadim V. Nikulin [b], Arno Villringer [a,b], and Michael Gaebler [a,b]

[a] *Berlin School of Mind and Brain, Humboldt-Universität zu Berlin, Germany*

[b] *Department of Neurology, MPI for Human Cog. and Brain Sci., Leipzig, Germany*

[c] *Sussex Neuroscience, University of Sussex, Brighton, UK*

[d] *Amsterdam Brain and Cognition (ABC), University of Amsterdam, Netherlands*

MAX-PLANCK-GESELLSCHAFT

** equal contribution* a.mariola@sussex.oc.uk, klotzsche@cbs.mpg.de, simon.hofmann@protonmail.com

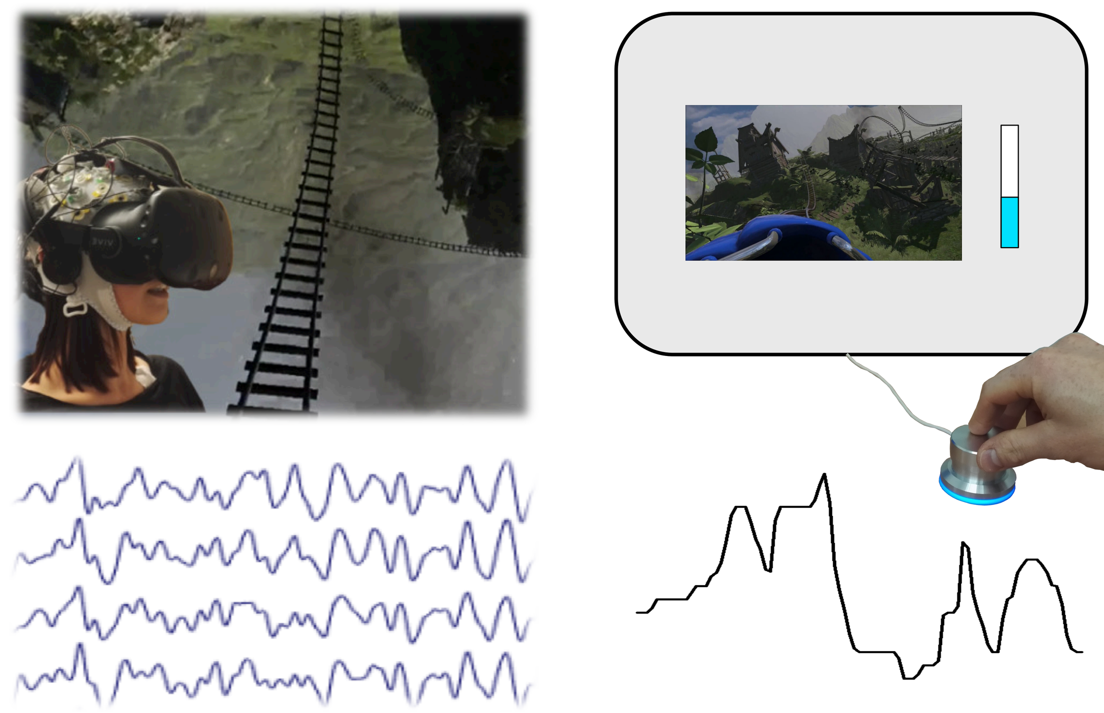
MAX PLANCK INSTITUTE FOR HUMAN COGNITIVE AND BRAIN SCIENCES LEIPZIG

Introduction

Arousal is a *core* affect constituted of both bodily and subjective states that prepares an agent to respond to events of the natural environment [1]. While the peripheral physiological components of arousal have been examined also under naturalistic conditions [2], its neural correlates were suggested mainly on the basis of simplified experimental designs [3].
We used virtual reality (VR) to present a highly immersive and contextually rich scenario of roller coaster rides to evoke naturalistic states of emotional arousal. Simultaneously, we recorded EEG to validate the suggested neural correlates of arousal in alpha frequency oscillations (8-12Hz) over temporo-parietal cortical areas [3]. To find the complex link between these alpha components and the participants' continuous subjective reports of arousal, we employed a set of complementary analytical methods coming from machine learning and deep learning.

Paradigm

1



t_0 *EEG measurement during VR roller coaster experience*

t_1 *continuous rating of subjective emotional arousal during replay*

Methods

Participants
38 (20♀) healthy, young (range: 18-35 years) adults

Stimulation
HTC Vive Head-mounted Display

Measurement
30 channel EEG (BrainProducts LiveAmp + actiCap)

Task (Fig1)

t_0 passive viewing of two immersive virtual roller coaster rides [4] + intermediate 30s break (stable head-position)

t_1 retrospectively: continuous rating of subjective emotional arousal during the prior VR episode based on a replay of the roller coaster episodes

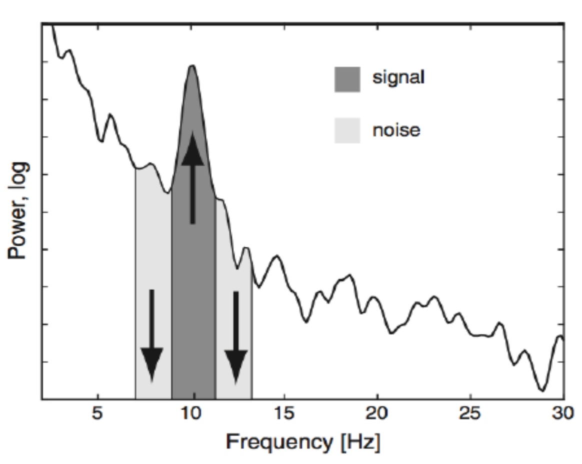
EEG Analysis

Preprocessing
PREP pipeline [5], EOG activation removal

Dimensionality reduction
Spatio-spectral decomposition (SSD) [6]
(Fig2 by [6])

2

- *optimized signal-to-noise ratio for a specified frequency band of interest, here:*
- ***central alpha 8-12Hz*** (↑)



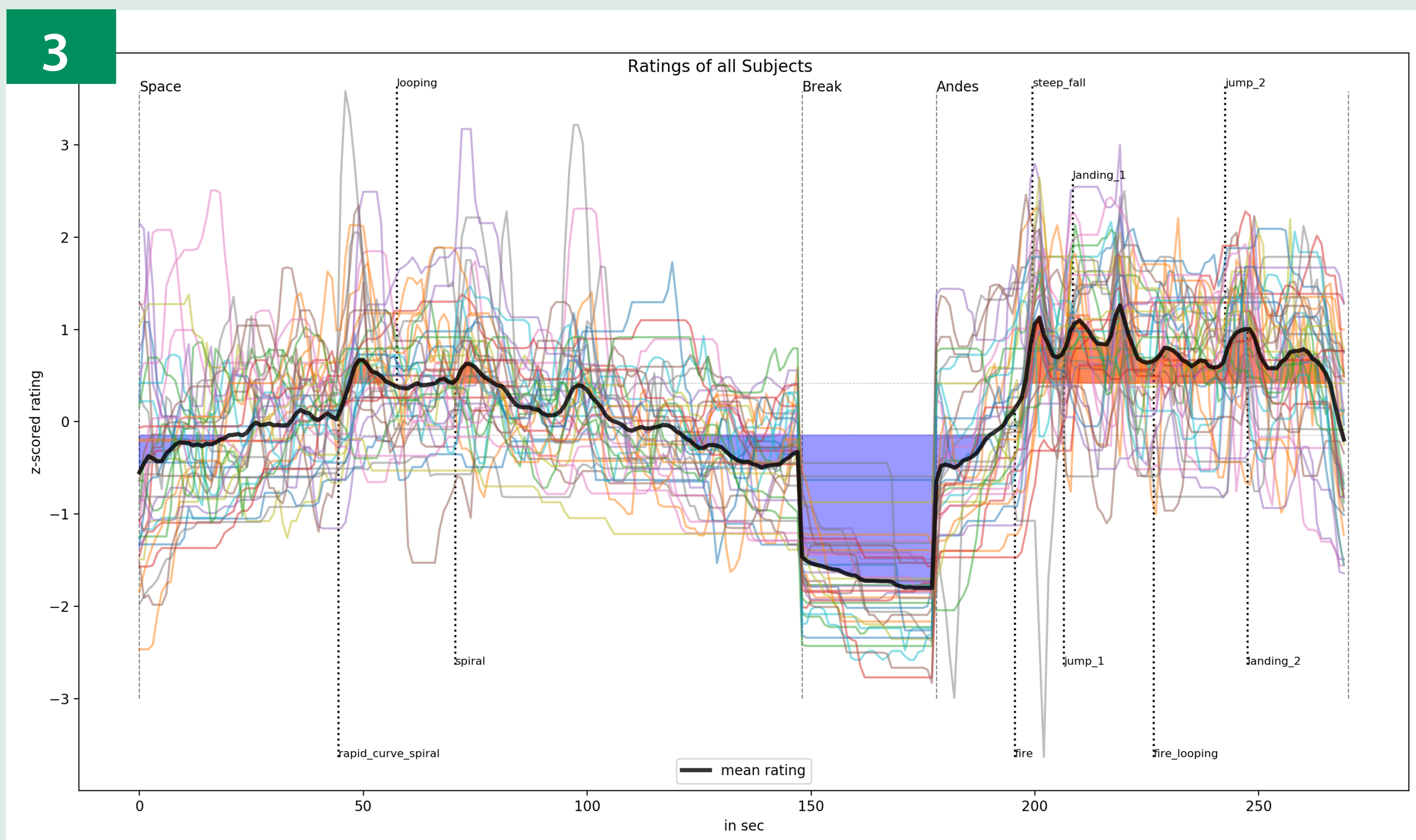
Prediction

Aim
Using the alpha components of the EEG data to predict for each single moment (second) the reported level of arousal.

Ground truth (Fig3)
- individual behavioural ratings
- tertile split of individual time series: high & low arousal

Two approaches
- binary classifier (CSP, LSTM) of low & high arousal
- regression models (SPoC, LSTM)

3

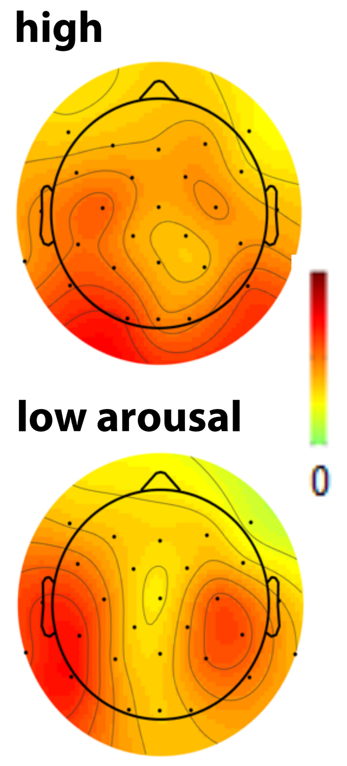


Analysis approaches & Results

Common spatial patterns (CSP) [7]
- derives a set of spatial filters to project the EEG data onto components whose band-power maximally relates to the prevalence of a specified class (e.g., high vs. low arousal).
- discriminate between two classes of mental states
- extracted feature: bandpower of 6 most discriminative components (1sec windows)

Results CSP – Binary Classification
- **Avg. accuracy: 63.8%** (SE=0.99%) sign. above chance level (p<.001, CI: .57-1)
- Avg. spatial activation patterns (Fig4)

4



Long Short-Term Memory (LSTM) recurrent neural nets [8]
- detect short & long-term dependencies in time series
- hyperparameters (e.g., layers, activation function) found via random search strategy [9] (Fig5)
- Model inputs: SSD alpha components ($LSTM_{SSD}$) benchmarked with SPoC components ($LSTM_{SPoC}$)

Results $LSTM_{SSD}$ – Binary Classification / Regression
- binary classifier: **Avg. accuracy: 63.4%** sign. above chance lvl. ($perm_{3000}$ p<.001, range .514–.816)
- regression: sign. above mean-accuracy-line (diff=.046, $perm_{3000}$ p<.001, range .03–.173)
- in both tasks no sign. difference between $LSTM_{SSD}$ and $LSTM_{SPoC}$ (binary classification: $perm_{3000}$ p=.554; regression: $perm_{3000}$ p=.735)

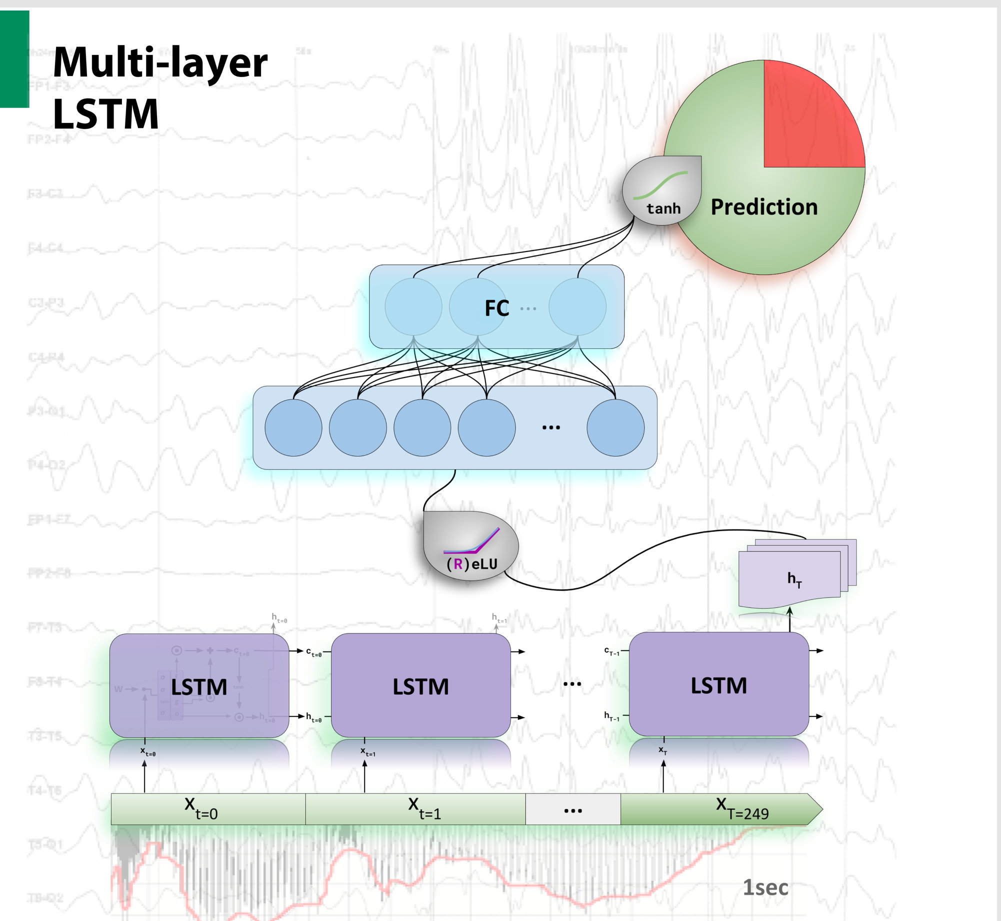
Source Power Comodulation (SPoC) [10]
- extracts functionally relevant EEG components by maximising the correlation of their bandpower with the continuous ground truth (here: ratings, Fig3)
- SPoC was computed over the 5 best SSD components of each participant

Results SPoC – Regression
- **Avg. correlation coefficients** for single best components sign. lower than zero (mean r =-.20, CI: -.28, -.12, p<.001)
- 84% of them were negative (32/38)
- 39% of them (15/38) remained sign. (p<.05) after bootstrapping iterations (n=500)

Summary & Discussion

- Power fluctuations in the alpha range (8-12 Hz), particularly in temporo-parietal areas, predict subjective ratings of emotional arousal
- Our results extend previous findings of simplified experimental designs [3] regarding emotional arousal to more ecologically valid settings
- These findings are consistent across the applied complementary set of methods in binary classification and continuous prediction
- Integrating different machine learning methods with VR immersive technologies provides a promising toolset towards a better understanding of human subjective experience in natural conditions

5 **Multi-layer LSTM**



Code open-source github.com/SHEscher/NeVRo

Acknowledgments

Thanks to Cade McCall, Alireza Tarikhi, Mert Akbal, Nicolas Endres, and Firat Sansal for their contributions.

References

[1] Russell & Feldman Barrett (1999). *Journal of Personality and Social Psychology*, 76(5), 805–819.
[2] McCall et al. (2015). *Consciousness and Cognition*, 38, 60–70.
[3] Di Bernardi Luft & Bhattacharya (2015). *Scientific Reports*, 5, 1–11.
[4] Russian VR coasters (2016). http://store.steampowered.com
[5] Bigdely-Shamlo et al. (2015). *Frontiers in Neuroinformatics*, 9, 1–20.
[6] Nikulin et al. (2011). *NeuroImage*, 55(4), 1528–1535.
[7] Blankertz et al. (2008). *IEEE Signal Processing Mag.*, 41–56.
[8] Hochreiter & Schmidhuber (1997). *Neural Computation*, 9(8), 1735–1780.
[9] Bergstra & Bengio (2012). *Jour. of Mach. Learn. Res.* 13, 281–305.
[10] Dähne et al. (2014). *NeuroImage*, 86, 111-122.

MindBrainBody Symposium, 2018