# Extracting Motion-Related Subspaces from EEG in Mobile Brain/Body Imaging Studies Using Source Power Comodulation

Lukas Gehrke *[1], Luke Guerdan *[2], Klaus Gramann [1,3,4]

* Denotes equal contribution.

1. Department of Biopsychology and Neuroergonomics, TU Berlin, Strasse des 17. Juni 135, 10623 Berlin, Germany lukas.gehrke@tu-berlin.de
2. College of Engineering, University of Missouri, Columbia, Missouri, USA lmg4n8@mail.missouri.edu
3. Center for Advanced Neurological Engineering, University of California San Diego, USA
4. School of Software, University of Technology Sydney

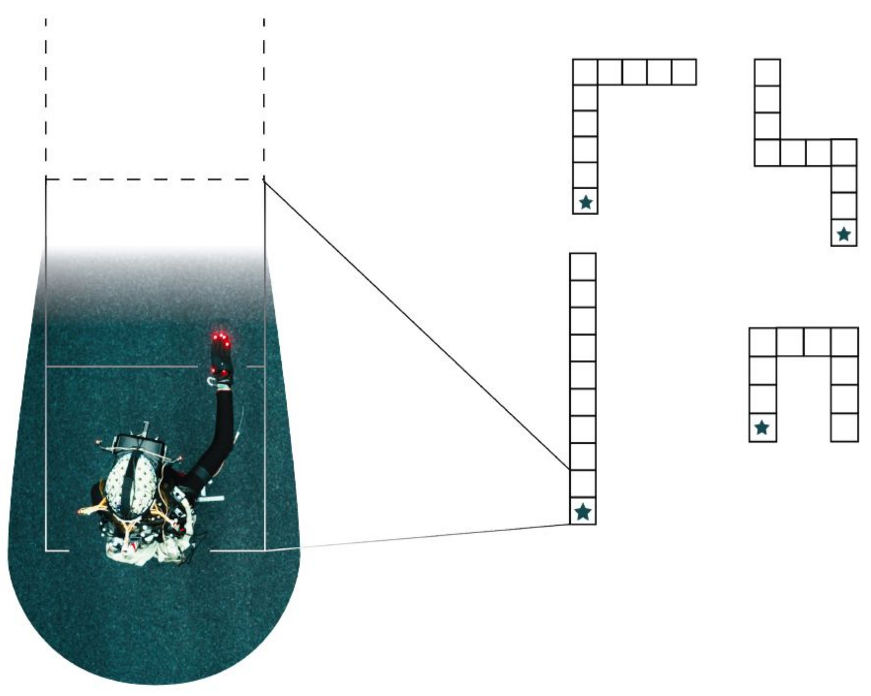
## Introduction

- Recent trends in neuroscience propose to move from stationary to **unconstrained experimental setups** [1,2].
- Unconstrained setups can provide insight as to how sensory movement signals (proprioception, vestibular organs, changes in auditory landscape) are integrated during natural cognition/navigation [3].
- **Mobile Brain/Body Imaging (MoBI)** is an approach to combine **VR stimulation**, **motion capture**, and **electroencephalography (EEG)**, providing unique multimodal datasets.
- Traditional late fusion analysis approaches of linking brain and behavior can be complemented by novel **early fusion data-driven machine learning**.

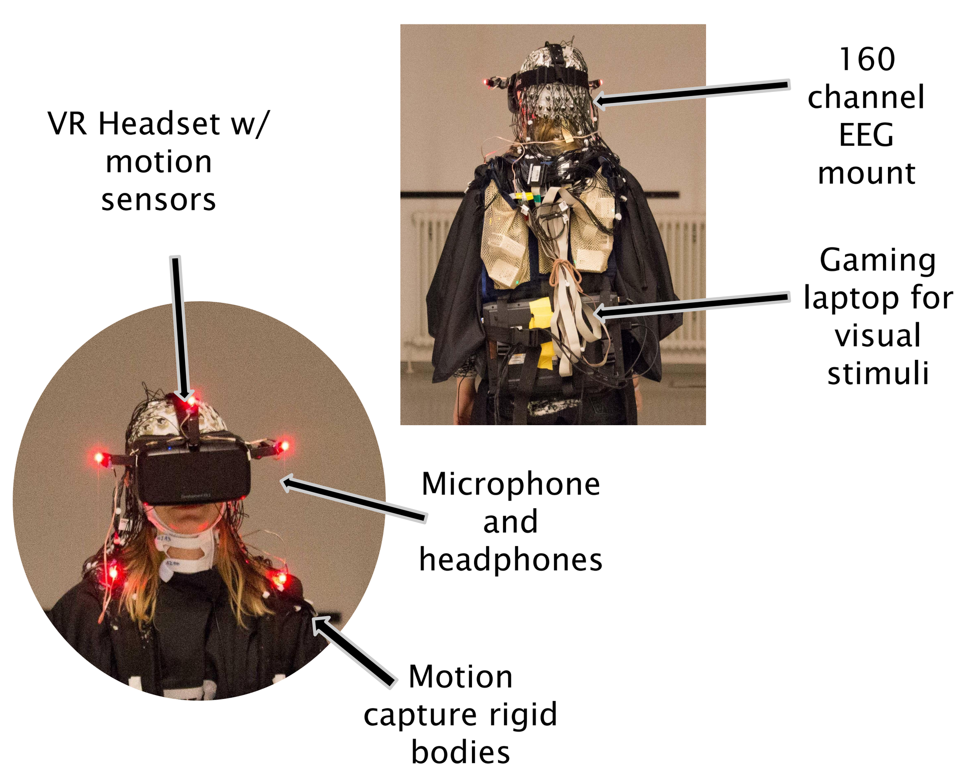
## Methods

- **Source Power Co-modulation (SPoC)**: make unsupervised blind source separation (BSS) more accurate by introducing a target variable (supervised learning). Prefer components whose power co-modulates with the target variable [4].
- **Spatio-spectral Decomposition (SSD):** maximize the signal power at a peak frequency while simultaneously minimizing it at the neighboring, surrounding frequency bins [5].
- Target signals were constructed using instantaneous velocity and acceleration of the hand rigid body as participants navigated in the Invisible Maze Task [6].
- We develop an end-to-end pipeline to evaluate these approaches compared with linear regression, testing multiple motion profiles and EEG frequency ranges.
- Components were excluded if they (a) had an inconsistent correlation sign across validation folds, or (b) were flagged by SASICA as displaying focal topology or high autocorrelation.
- Spearman correlation between the estimated source component and actual target signal was computed as part of a 5-fold cross validation experiment.

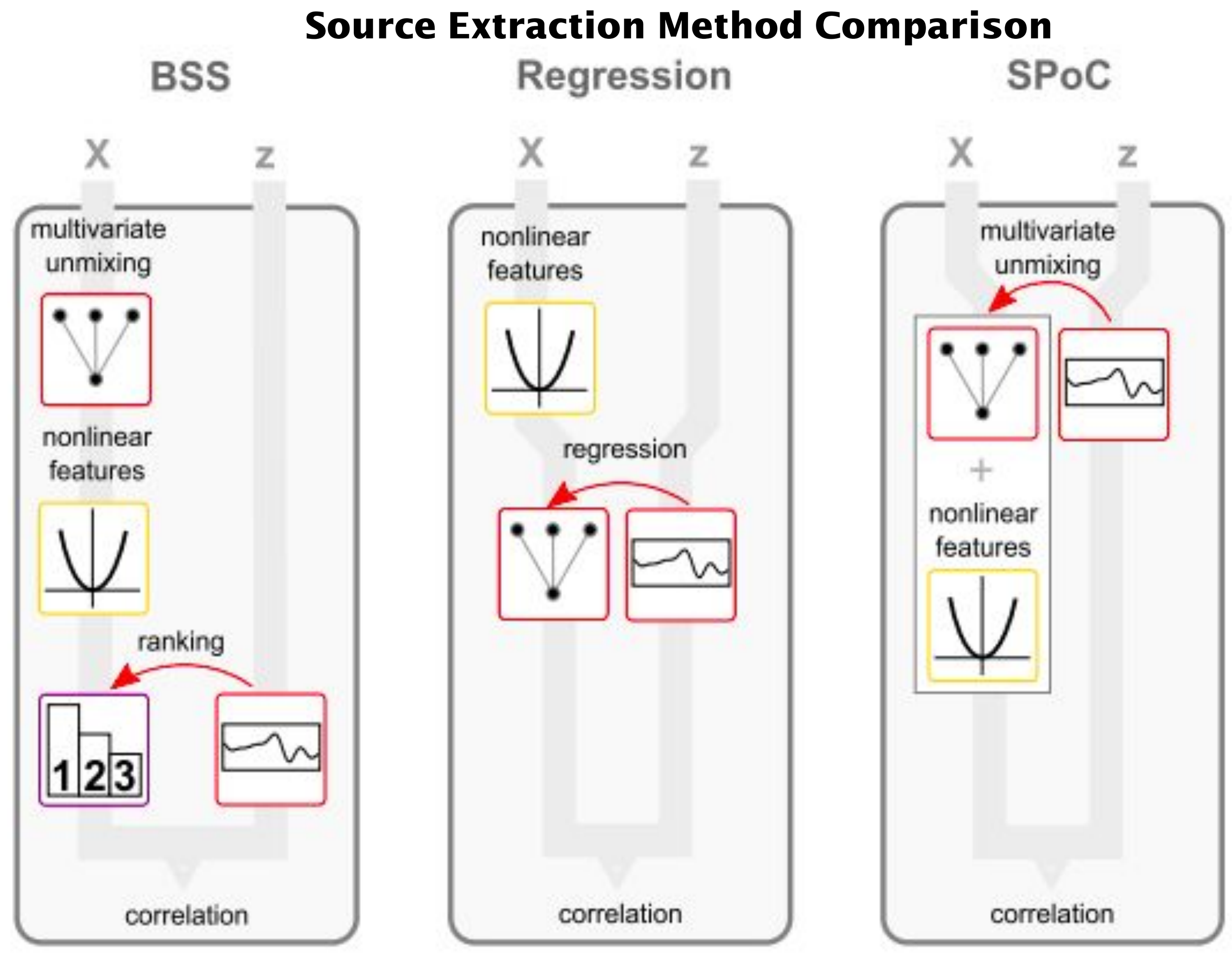
### Virtual Maze Paradigm



### MoBI Experimental Setup

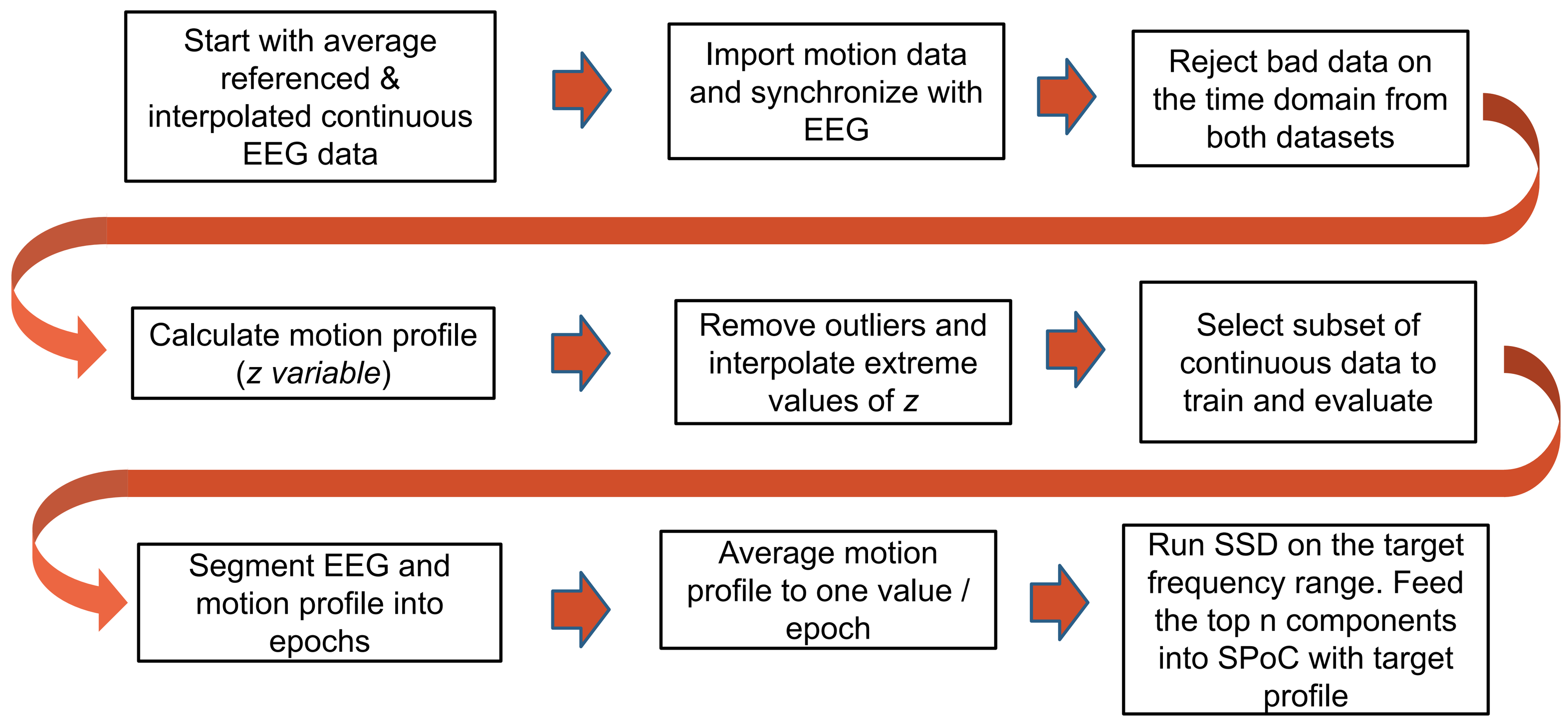



### Source Extraction Method Comparison




Dähne, S. October 6th, 2015, *Decomposition methods for the fusion of multimodal neuroimaging data*, http://dx.doi.org/10.14279/depositonce-4683

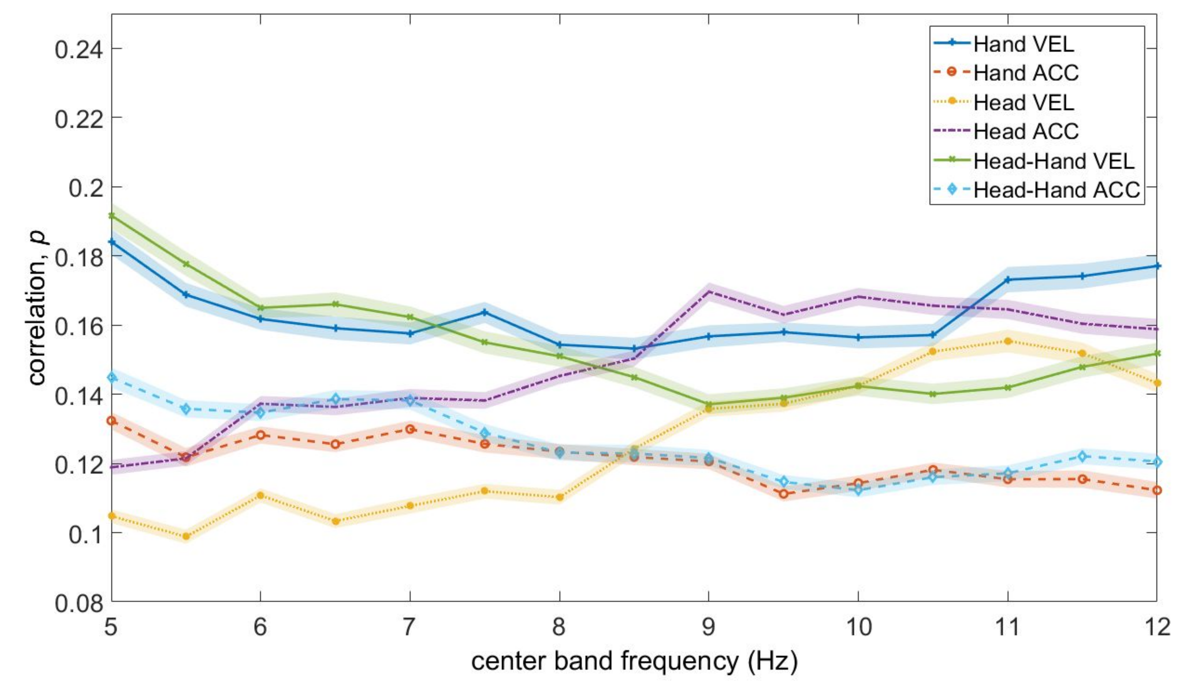
### The SPoC Analysis Pipeline



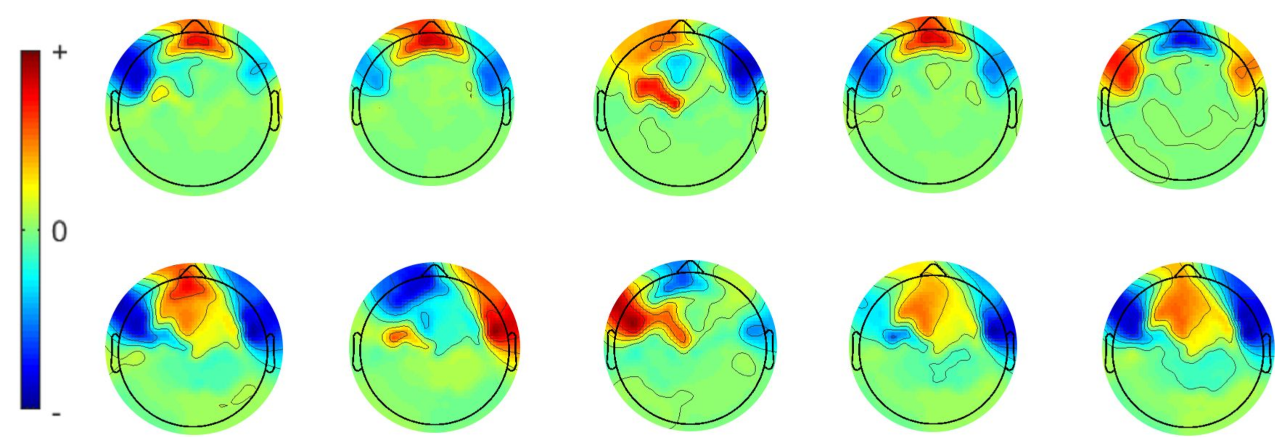

## Results

- Across all configurations SPoC (median $\rho_{mean}$ = 0.13) out performed the regression-based approach (median $\rho_{mean}$ = 0.9).
- Overall 865 of the total 13050 possible SPoC components passed the SASICA selection criteria with a median $\rho_{mean}$ = .16
- A high degree of variability exists between subjects in the number and quality of components extracted.

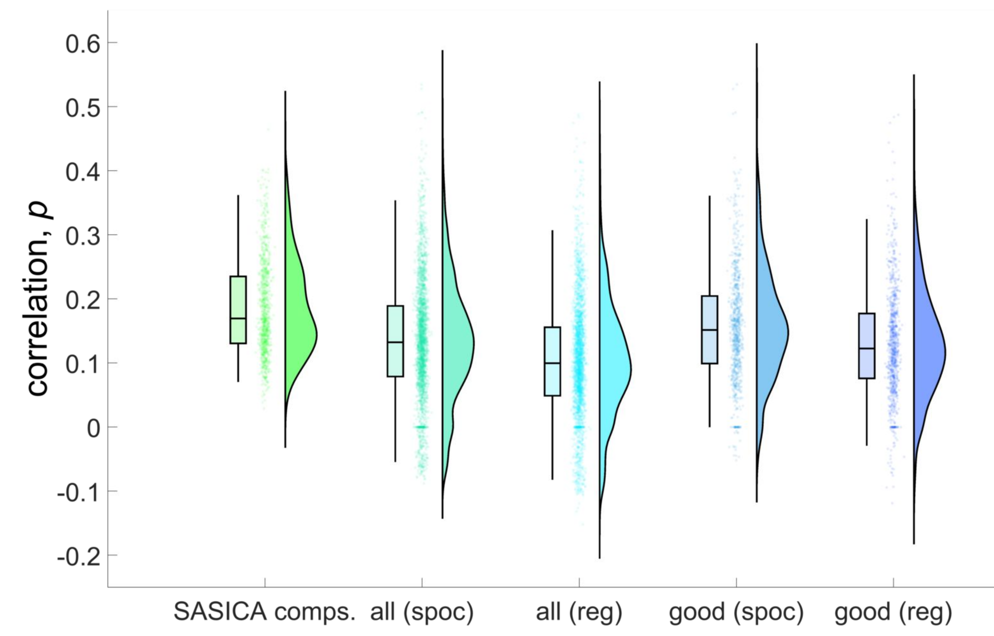
### Component Correlations Across Band Frequencies and Profiles




### Example Component Scalp Topographies



### Correlations of SPoC vs Linear Regression Components




## Discussion

- Component selection may be improved/standardized by considering consistency and plausibility of spatial filters. This may be applied through a similarity metric or human manual inspection.
- Whereas ICA can isolate localizable dipoles, SPoC finds components of functional significance. Using distributed source localization methods it may be possible to combine both approaches to retrieve localizable sources of functional significance.

## References

[1]Gramann, K., Ferrisc, D.P., Gwinc, J., and Makeig, S. (2014). Imaging natural cognition in action. *International Journal of Psychophysiology* **91** (1), 22-29.

[2]Makeig, S., Gramann, K., Jung, T., Sejnowski, T., Poizner, H.(2009). "Linking brain, mind and behavior", International Journal of Psychophysiology, 73, pp 95–100.

[3]Wilson, M., (2002) "Six views of embodied cognition", Psychonomic Bulletin & Review, **9** (4), 625-636.

[4]Dähne, S., Meinecke, F., Haufe, S., Hhne, J., Tangermann, M., Mller, K. and Nikulin, V. (2014). SPoC: A novel framework for relating the amplitude of neuronal oscillations to behaviorally relevant parameters. NeuroImage, 86, pp.111-122.

[5]V. Nikulin, G. Nolte and G. Curio. (2011). "A novel method for reliable and fast extraction of neuronal EEG/MEG oscillations on the basis of spatio-spectral decomposition", Klinische Neurophysiologie, vol. 42, no. 01.

[6]Gehrke L., Iversen J.R., Makeig S., Gramann K. (2018) The Invisible Maze Task (IMT): Interactive Exploration of Sparse Virtual Environments to Investigate Action-Driven Formation of Spatial Representations. In: Creem-Regehr S., Schöning J., Klippel A. (eds) Spatial Cognition XI. Spatial Cognition 2018. Lecture Notes in Computer Science, vol 11034. Springer, Cham