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]

***Abstract*— Mobile Brain/Body Imaging (MoBI) is an emerging non-invasive approach to investigate human brain activity and motor behavior associated with cognitive processes in natural conditions. MoBI studies and analyses pipelines combine brain measurements, e.g. Electroencephalography (EEG), with motion data as participants conduct tasks with near-natural behavior. However, within this field, standard source decomposition and reconstruction pipelines largely rely on unsupervised blind source separation (BSS) approaches and do not consider movement information to guide the decomposition of oscillatory brain sources. We propose the use of a supervised spatial filtering method, Source Power Co-modulation (SPoC), for extracting source components that co-modulate with body motion. Further, we introduce a method to validate the quality of oscillatory sources in MoBI studies. We illustrate the approach to investigate the link between hand and head movement kinematics and power dynamics of EEG sources while participants explore an invisible maze in virtual reality. Stable oscillatory source envelopes correlating with hand and head motion were isolated in all subjects, with median $\rho = .13$ for all sources and median $\rho = .16$ for sources passing the selection criteria. The results indicate that it is possible to improve movement related source separation to further guide our understanding of how movement and brain dynamics interact.**

I. INTRODUCTION

A key aspect of better understanding normal and pathological brain function is investigating the brain dynamics of humans as they act in their natural environments. Non-invasive recordings of brain dynamics during ongoing unrestricted movements can provide valuable insight into the interplay between locomotion and mental processes, providing an enhanced understanding of spatial cognition, movement disorders, and rehabilitation approaches. However, investigating and analyzing human brain activity during active behavior in naturalistic conditions remains a fundamental challenge for established brain imaging approaches. Mobile Brain/Body Imaging (MoBI [1], [2]) is one approach leveraging multimodal data acquisition and analyses pipelines to overcome restrictions of traditional brain imaging methods that require participants to move as little as possible.

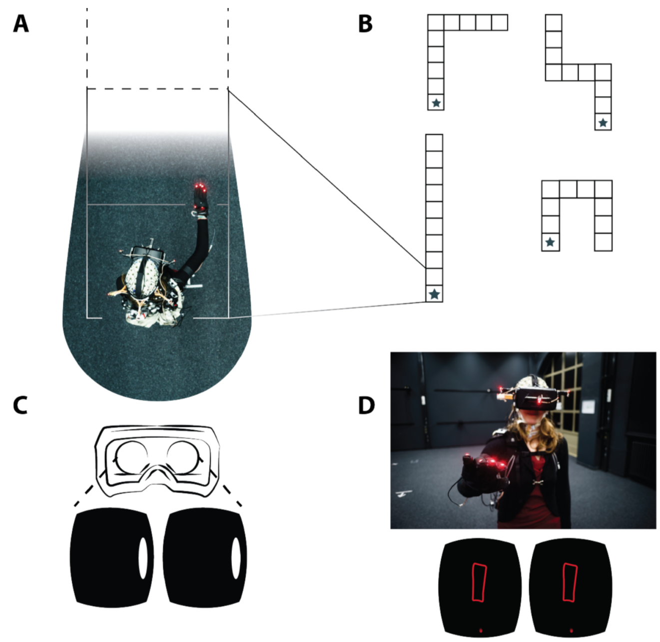

Fig. 1. Invisible Maze Task, **A** Participant from a birds eye view. **B** Participants are instructed to explore four different mazes and return to the start. **C** First-person view in binocular "VR optics" of a wall touch. **D** Top: Participants draw a top-down view of the explored maze. Participant is equipped with 160 channels wireless EEG, head-mounted virtual reality goggles and LEDs for motion capture. Bottom: drawn sketch map. Find a detailed description in [5].

Due to its high temporal resolution and lightweight hardware, Electroencephalography (EEG) is the most prominent method of acquiring and interpreting complex brain dynamics in moving participants. EEG measures the electrical activity of the brain through sensors placed on the scalp and, after processing, the measured oscillatory activity may be linked to sensory, cognitive, and motor processes [3]. One challenge of using EEG is the diminished signal to noise ratio when participants move through space, as natural movement causes severe artifacts challenging the isolation of sources of interest. Current approaches address this challenge by applying blind source separation (BSS), a process in which sources are estimated in an unsupervised manner [3], [4]. A major drawback of using BSS methods such as Independent Components Analysis (ICA) is that they do not consider motion information while estimating source components. Considering motion information poses the advantages of (1) extracting sources functionally related to the task of interest (in MoBI settings), (2) improving the signal-to-noise ratio,

*Denotes equal contribution.

This research was supported by a grant from the German Federal Ministry of Education and Research (01GQ1511) to KG

[1]Lukas Gehrke and Klaus Gramann are with Department of Biopsychology and Neuroergonomics, TU Berlin, Strasse des 17. Juni 135, 10623 Berlin, Germany `lukas.gehrke@tu-berlin.de`

[2]Luke Guerdan is with the 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, USA

and (3) isolating artifactual sources related to task irrelevant motion information.

We propose the use of a supervised spatial filtering method to find oscillatory sources related to hand and head kinematics. We apply this method to extract source components as participants conduct the Invisible Maze Task (IMT)–a MoBI experiment in which participants navigate visually sparse mazes in virtual reality (VR) [5]. Extracted components are shown to correlate with motion profiles across different frequency ranges. We discuss an application in which extraction of sources using movement information helps addressing questions about movement influencing cognitive phenomena.

II. Methods

The Generative Model of EEG. Let the electromagnetic field recordings measured by N_x EEG channels over t time points be represented by the multivariate variable $\mathbf{x}(t) \in \mathbb{R}^{N_\text{x}}$. Further, let there be N_s unknown neural sources, where $\mathbf{s}(t)$ expresses the activity of sources across time. The generative model projecting sources to observed channels can be expressed linearly as:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \tag{1}$$

where $\mathbf{A} \in \mathbb{R}^{N_\text{x} \times N_\text{s}}$ contains a spatial pattern $\mathbf{a} \in \mathbb{R}^{N_\text{x}}$ corresponding to a source component in each column. An estimate for each underlying source $\hat{\mathbf{s}}_i(t)$ can be computed using $\mathbf{w} \in \mathbb{R}^{N_\text{x}}$ such that $\hat{\mathbf{s}}_i(t) = \mathbf{w}_i{}^\mathbf{T}\mathbf{x}(t)$, where the spatial filter $\mathbf{w}$ projects from sensor space to source space. BSS approaches estimate the factors $\mathbf{A}$ and $\mathbf{s}(t)$ jointly through an unsupervised process using a criteria such as minimizing mutual information between sources.

Source Power Co-modulation. An alternative to unsupervised BSS methods is using a supervised spatial-filtering approach that leverages a continuous target variable z during the decomposition. Source Power Co-modulation [6] is one such method designed to find a spatial filter projecting the data onto an estimated source component in which the band power of $\hat{\mathbf{s}}(t)$ co-modulates with z optimally. We assume that the EEG data has been segmented into e epochs $\mathbf{x}(e)$, and that z is downsampled to one value per epoch $z(e)$. Provided that $\mathbf{x}(t)$ has been bandpass filtered to a narrow frequency range, we can compute an estimate of the epoched target variable $z(e) \approx \phi(e)$ = Var[$\mathbf{w}^\mathbf{T}\mathbf{x}$] using the spatial filter $\mathbf{w}$. The objective function solving for the optimal spatial filter $\mathbf{w}$ can then be defined as $\arg\max_w$ Cov[$\phi(e), z(e)$], subject to the constraint that $\mathbf{w}$ has unit variance. The resulting algorithm is referred to as SPoC$_\lambda$ and returns eigenvectors forming each spatial filter $\mathbf{w_i}$ and corresponding eigenvalues ordered by covariance score. Since SPoC adheres to the generative model outlined above, spatial patterns can be recovered by multiplying the average covariance matrix $\mathbf{C}_\text{x}$ of $\mathbf{x}(e)$ such that $\mathbf{a}_i = \mathbf{C}_\text{x}\mathbf{w}_i$.

Dimensionality reduction of EEG data prior to applying SPoC was performed to reduce overfitting and to simplify the proceeding component selection step. A key assumption of SPoC$_\lambda$ is that the input EEG data has been filtered to within a narrow target frequency range of interest. We first filtered the input data to the target frequency range, then performed dimensionality reduction using spatio-spectral decomposition (SSD) [7]. SSD maximizes the signal profile at a frequency band of interest while simultaneously minimizing it in the neighboring bands and has been shown to support the extraction of oscillatory components [8]. We retained the first 10 SSD components and disregarded the remaining ones, leaving a 10 dimensional oscillatory subspace corresponding to the target frequency range. Epoch size, number of SPoC components to retain, and number of epochs to train on were optimized using a parameter grid search.

Frequency and motion profile parameter selection. Head kinematics have been linked to alpha and beta wave activity [9]; however, it remains a challenge to unravel which motion properties of the hand and head and specific frequency ranges are involved in moving participants exploring the surrounding space. To investigate the co-modulation of hand and head motion with oscillatory sources across frequency bands and different kinds of motion, we performed a search across theta and alpha frequency ranges for six different motion profiles: magnitude of hand velocity and acceleration, magnitude of head velocity and acceleration, and magnitude of head minus hand velocity and acceleration. Magnitude of velocity and acceleration profiles were calculated by taking the magnitude of the instantaneous velocity and instantaneous acceleration of the x, y, and z rigid body coordinates, respectively. Similarly, head minus hand profiles were calculated by subtracting hand position from head position, then calculating instantaneous velocity and acceleration on the difference.

Each frequency band of interest $[f_0 - \Delta f,\ f_0 + \Delta f]$ was targeted by changing the SSD band settings, varying the center frequency range f_0 from 5-13 Hz and keeping $\Delta f = 1$ Hz constant. The flanking interval is set to $f_0 \pm 3$ Hz and the bandstop filter was fixed at $f_0 \pm 4$ Hz as suggested in [7]. Before performing SSD, a bandpass filter was applied to the frequency range of interest. Scanning over 6 motion profiles and 15 band settings resulted in 90 parameter configurations, which returned 10 SPoC$_\lambda$ components each due to the reduced data rank after application of SSD. To simplify further analysis, only the first five components were considered.

Evaluation Metrics. Spearman rank correlations were computed to quantify the degree to which estimated oscillatory components co-modulate with the target motion profile z. Since SPoC is a supervised learning algorithm, we employed chronological 5-fold cross-validation to control for overfitting [10]. In this scheme, four folds were used to train each SPoC filter $\mathbf{w}_i$ which was then applied to held-out validation data $\mathbf{x}(t)_\text{test}$ to get estimated source activations $\hat{\mathbf{s}}(t)_\text{test}$. The test correlation for fold i between $z_\text{aprox,i} = Var[\hat{\mathbf{s}}(t)_\text{test,i}]$, the band power approximation of $\hat{\mathbf{s}}$, and $(t)_\text{test}$ was then averaged across folds to get a mean correlation score for each component. All correlations reported below were calculated from folds withheld in $\hat{\mathbf{s}}(t)_\text{test}$.

In addition to correlation, the resulting SPoC components were evaluated based on several criteria to select robust sources. To ensure stability over time, the selection was limited to components whose correlation sign remained constant across folds as originally suggested in [11]. Additionally, objective criteria were applied to automatically flag components that displayed low autocorrelations or a focal topography, see SASICA toolbox [14]. Though SASICA was originally applied to ICA components, these settings also characterize desirable SPoC components. If a component was rejected by SASICA in any validation fold, it was rejected from further analysis.

Linear Regression Comparison. We added a comparison of the resulting SPoC components with linear regression on channel-level power features to evaluate SPoC$_\lambda$ against another supervised linear method.The same parameter grid search and cross validation scheme are used with both algorithms. Whereas SPoC returns components equal to the rank of the data, regression will only return one.

III. Experimental Setup

Participants. Thirty-two healthy participants (aged 21–45 years, 14 men) took part in the experiment. All participants gave written informed consent to participation and the experimental protocol was approved by the local ethics committee (protocol: GR_08_20170428). Three participants were excluded from data analysis due to incomplete data or difficulties in complying with the task requirements.

The Invisible Maze Task. Participants freely explored an interactive sparse invisible maze environment by walking and probing for virtual visual wall feedback with their hand, delivered by a virtual reality (VR) headset. Four different mazes (Fig. 1 B) were explored in three consecutive runs. Upon collision of the hand with an invisible wall, an illuminated white disc was displayed 30cm behind the collision point parallel to the invisible wall (Fig. 1 C). Due to the complexity of the technical details, please consult [5]. In summary, the task required participants to explore mazes to build a spatial representation of the maze layout.

Data Collection & Preprocessing. EEG was recorded using 160 actively amplified channels (BrainProducts MOVE System) using an equidistant 128 channel electrode placement cap and a 32 channel neck band (EasyCap); the reference electrode was placed between parietal electrodes and two vEOG electrodes were placed under each eye. Signals were sampled at 1kHz. Concurrent motion capture (6DOF, position and orientation) of six rigid bodies (head, hand, feet, lower and upper arm) was collected with a sampling rate of 75Hz. Both data streams were aligned[1], the age-of-sample of the EEG data was corrected (66ms)[2] and both datastreams were resampled at 250 Hz. We applied a 6 Hz zero-lag low pass FIR filter to smooth the motion data. After transforming quaternion orientation to Euler angles, we calculated time derivatives. Non-experimental segments containing only minimal movements of participants were removed from further analysis. Then, for EEG cleaning purposes, continuous data was split into 1s epochs and an automatic cleaning procedure was applied to remove the 10% noisiest epochs [9].

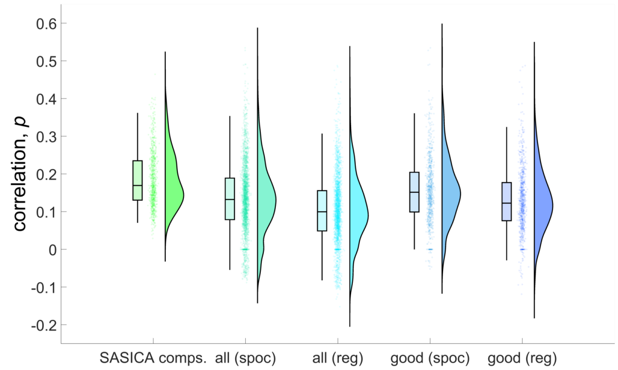

Fig. 2. Median correlation ρ achieved across configurations for SPoC$_\lambda$ and linear regression. Configurations from left to right: selected SPoC$_\lambda$ components (SASICA), components of all motion profiles, components of *good* motion profiles (magnitude of hand velocity and magnitude of head acceleration).

IV. Results.

The first 800 cleaned seconds of EEG and motion capture data from each participant were epoched into 1 second intervals and used for training SPoC$_\lambda$ as outlined above. The performance of SPoC$_\lambda$ and linear regression across parameter configurations and subjects is reported in Fig. 2 and Fig. 3. Fig. 2 reports the distribution of the highest-correlating SPoC$_\lambda$ components and all regression components across configurations and subjects. Across all configurations SPoC (median ρ_{mean} = .13) out performed the regression-based approach (median ρ_{mean} = .09). When limiting to the best-performing velocity and acceleration profiles, SPoC performance also surpassed the regression performance (ρ_{mean} = .15; ρ_{mean} = .12 respectively). Fig. 3 reports ρ_{mean} corresponding to the SPoC$_\lambda$ component with the highest correlation in each parameter configuration, with error bars representing one standard deviation across participants. Magnitude of head velocity performed best with an average test correlation across folds and subjects of $\rho = .1352$, followed by magnitude of the hand velocity with an average correlation of $\rho = .1348$. Head hand difference profiles performed worse than profiles consisting of only the head or the hand velocity.

Overall 865 of the total 13050 possible SPoC$_\lambda$ components passed the SASICA selection criteria with a median ρ_{mean} = .16. There was a high variability in the number of components selected across participants. First–ranked SPoC components were more–often selected compared to later–ranked ones, and better–performing motion profiles are also more likely to pass selection criteria. Fig. 4 displays exemplary scalp topographies obtained from one of the participants with the most passing components across folds.

[1]https://github.com/sccn/labstreaminglayer

[2]http://bemobil.bpn.tu-berlin.de/wiki/doku.php?id=software:lsl-test

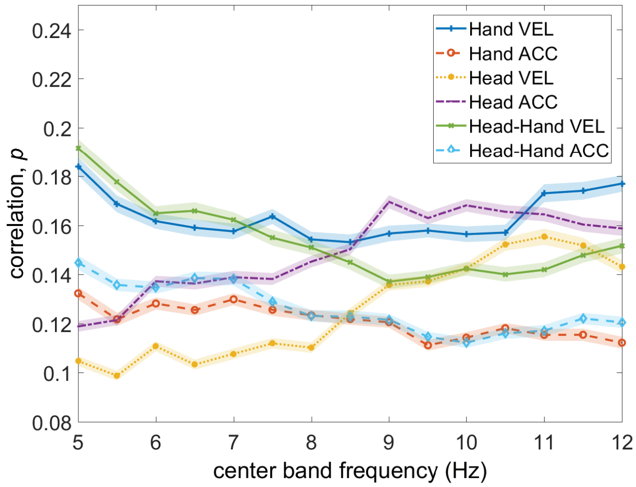

Fig. 3. Correlation ρ_{mean} of highest-correlating SPoC component (SPoCλ) across profiles and frequencies. Error areas indicate the standard error of the mean (SEM).

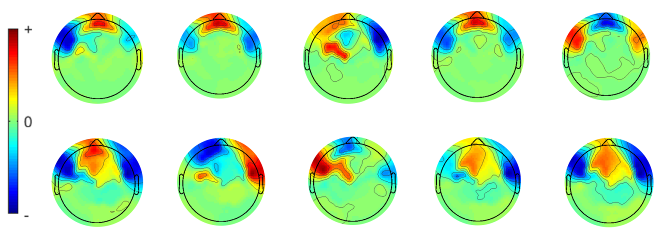

Fig. 4. Example spatial patterns across chronological folds with power spectra. **Top:** subject 22, f_0 = 7Hz, Magnitude of head acceleration. **Bottom:** subject 27, f_0 = 11 Hz, Magnitude of hand velocity.

V. Discussion.

Overall, we observed a positive relationship between filter consistency across folds, passing selection criteria, and the correlation value achieved. The correlation values we obtained are similar to those found in other applications of SPoC [11], [12]. Furthermore, we found similar filters across subjects albeit with slight variation in their center frequency. This suggests that similar to other methods, SPoC is sensitive to inter-subject frequency variability as well as differences in EEG recording quality.

To address questions of neuroscientific inquiry researchers may intervene in the component selection process. To improve consistency and plausibility of spatial filters regarding the focus of research inquiry, similarity metrics and human manual inspection based on a-priori assumptions about topographies or expected co-modulation behavior may still prove beneficial. The purpose of SPoC is not to isolate a single source, but to find a subspace in which a combination of sources co-modulate with a target variable. This introduces a tradeoff–whereas BSS methods, e.g. ICA, may isolate localizable dipoles with little residual variance[13], SPoC finds components of functional significance. However, distributed source localization procedures allow the interested researcher to localize sources of functional significance [15]. Such an approach may be of significant interest in MoBI studies aiming at a differentiation of frequency bands and specific motion profiles across source components as introduced here.

This work proposes a method for extracting robust motion-related source components in MoBI experiments. Either, the extracted sources may be of direct interest to the researcher or can be removed to clean the EEG recording from muscle, since muscle activity is inherently tied to body movement [3], or other movement co-modulating phenomena. For instance, eye movement and electromyography data streams may serve as target signals in SPoC directly reflecting specific muscle activity. In conclusion, SPoC is a promising method for extracting oscillatory sources that co-modulate with body motion in MoBI experiments. SPoC components can be selected based on objective criteria and used to investigate brain and muscle responses as participants act in natural environments.

References

[1] S. Makeig, K. Gramann, T.-P. Jung, T. Sejnowski, H. Poizner ”Linking brain, mind, and behavior.”, International Journal of Psychophysiology, 69(3), p.137, 2008.

[2] K. Gramann, T.-P. Jung, D.P. Ferris, C.-T. Lin, S. Makeig, ”Toward a new cognitive neuroscience: modeling natural brain dynamics.”, Frontiers in Human Neuroscience, 8:444, 2014.

[3] P. Reis, F. Hebenstreit, F. Gabsteiger, V. von Tscharner, M. Lochmann, ”Methodological aspects of EEG and body dynamics measurements during motion.” Frontiers in Human Neuroscience, 8, 2014.

[4] J. T. Gwin, K. Gramann, S. Makeig, and D. P. Ferris ”Removal of Movement Artifact From High-Density EEG Recorded During Walking and Running”, Journal of Neurophysiology, 103:6, 3526-3534, 2010.

[5] L. Gehrke, J.R. Iversen, S. Makeig, K. Gramann ”The Invisible Maze Task (IMT): Interactive Exploration of Sparse Virtual Environments to Investigate Action-Driven Formation of Spatial Representations”, Springer International Publishing, pp.293–310, 2018.

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

[7] V. Nikulin, G. Nolte and G. Curio, ”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, 2011.

[8] S. Haufe, S. Daehne and V. Nikulin, ”Dimensionality reduction for the analysis of brain oscillations”, NeuroImage, vol. 101, pp. 583-597, 2014.

[9] K. Gramann, F. U. Hohlefeld, L. Gehrke, M. Klug ”Heading computation in the human retrosplenial complex during full-body rotation”, biorXiv, doi:10.1101/417972, 2018.

[10] S. Lemm, B. Blankertz, T. Dickhaus and K. Mller, ”Introduction to machine learning for brain imaging”, NeuroImage, vol. 56, no. 2, pp. 387-399, 2011.

[11] A. Meinel, S. Castano-Candamil, J. Reis and M. Tangermann, ”Pre-Trial EEG-Based Single-Trial Motor Performance Prediction to Enhance Neuroergonomics for a Hand Force Task”, 2016.

[12] A. Meinel, J. Castano-Candamil, S. Daehne, J. Reis and M. Tangermann, ”EEG Band Power Predicts Single-Trial Reaction Time in a Hand Motor Task”, 7th Annual International IEEE EMBS Conference on Neural Engineering, 2015.

[13] A. Delorme, J. Palmer, J. Onton, R. Oostenveld, S. Makeig, Independent EEG sources are dipolar. PLoS ONE, e30135, 7(2), 2012.

[14] M. Chaumon, D. Bishop and N. Busch, ”A practical guide to the selection of independent components of the electroencephalogram for artifact correction”, Journal of Neuroscience Methods, vol. 250, pp. 47-63, 2015.

[15] T. O. Zander, L. R. Krol, N. P. Birbaumer, K. Gramann ”Neuroadaptive technology enables implicit cursor control based on medial prefrontal cortex activity.”, Proceedings of the National Academy of Sciences of the United States of America, 113(52), 1489814903., 2016.