Informative Oscillatory EEG Components and their Persistence in Time and Frequency

Michael Tangermann and Andreas Meinel
Brain State Decoding Lab, Cluster of Excellence BrainLinks-BrainTools, Department of Computer Science, Albert-Ludwigs-University of Freiburg, Albertstr. 23, Freiburg im Breisgau, Germany

Keywords: Electroencephalogram, EEG, Oscillatory Component, Oscillatory Subspace, Hyperparameter Optimization, Brain-Computer Interface, Common Spatial Patterns, CSP, Source Power Comodulation, SPoC, Visualization, Characterization, Tracking.

Abstract: Oscillatory brain activity measured by the electroencephalogram, local field potentials or magnetoencephalogram can reflect cognitive processes. It can be used to run brain-computer interfaces or to analyze information processing, user learning and rehabilitation progress, e.g., after stroke. To extract oscillatory components, which are informative about a users task and which show an enhanced signal-to-noise compared to raw multivariate recordings, data-driven spatial filtering methods are widely applied. Some of these approaches can learn spatial filters from labeled data. They typically require the data analyst to at least define a frequency band of interest and time interval relative to the course of events in the experiment. These hyperparameters are exploited by the filtering method in order to extract informative oscillatory features. Their choice typically is domain-specific and may require adaptations to individuals. Post-hoc data analysis, however, should not be restricted to the initial hyperparameter ranges. Thus we present an approach, which allows to characterize a given oscillatory component with respect to the frequency bands and the temporal windows for which it contains task-relevant information. The approach allows to track task-informative persistence of components over multiple experimental sessions and may be helpful to monitor motor learning and rehabilitation over time.

1 INTRODUCTION

Neurotechnological applications like brain-computer interface (BCI) systems for patients or non-medical use (Wolpaw and Wolpaw, 2012; Höhne et al., 2014; van Erp et al., 2012) tap into multivariate brain signals. Their goal is to either drive an online application, or to monitor mental processes, which are informative about the tasks executed by the user. But also outside the field of BCI, oscillatory signal components of electrophysiological recordings like the magnetoencephalogram, the electroencephalogram (EEG), invasive recordings of the electrocorticogram or local field potentials have long been studied, as they can contain information about the user task or task performance (Klimesch, 1999). The exploitation of these oscillatory signal components, however, is not straight forward due to the low signal-to-noise ratio especially with non-invasive recordings. Here, sophisticated data driven machine learning methods (Müller et al., 2008) proved helpful to extract subspaces containing informative oscillations with enhanced signal-to-noise ratio. Among these methods, common spatial patterns (CSP) (Ramoser et al., 2000; Koles, 1991; Fukunaga, 1990) and variants thereof are widely used (Tangermann et al., 2012; Lotte and Guan, 2011). The algorithm allows to extract oscillatory components, which display contrastive behavior, e.g. event-related de-synchronization (ERD) and -synchronization (ERS) effects. These ERD/ERS effects are *time-locked* e.g. to the cueing time point of discrete motor tasks (Pfutscheller et al., 1997), and are extracted for a pre-selected frequency band. More recently, source power comodulation (SPoC) was proposed by Dähne and colleagues (Dähne et al., 2014) as a regressing subspace filtering approach. SPoC allows to extract oscillatory components from bandpass-filtered EEG, which comodulate in their band power amplitude with a known variable. This variable in practice can be derived e.g. from a task-wise behavioral metric or represent the intensity of stimuli. At training time, when spatial filters (they determine the oscillatory subspace components) are derived, an optimization problem needs to be solved. Depending on the algorithm, this can be time-consuming as it typically involves an iterative gra-

Tangermann M. and Meinel A.
Informative Oscillatory EEG Components and their Persistence in Time and Frequency.
In *NEUROTECHNIX 2017 - Extended Abstracts (NEUROTECHNIX 2017)*, pages 17-21

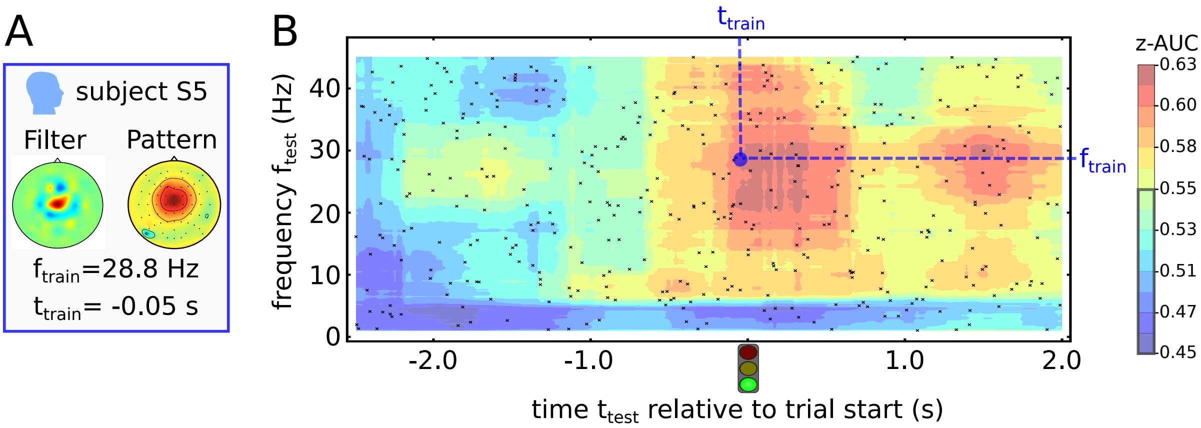

Figure 1: (a) Characterization of an exemplary oscillatory component (spatial filter and spatial pattern) derived by parameters (t_{train} = -50 ms, f_{train} = 28.8 Hz) using the source power comodulation (SPoC) method. (b) The z-AUC performance of this SPoC component for varying pairs of hyperparameters (t_{test}, f_{test}) sampled at coordinates marked by single black dots is interpolated and depicted in a color scheme. The chance level is provided by the blue-rimmed z-AUC values.

dient descent or the calculation of covariance matrices and their inversion. At testing time, however, the application of a known spatial filter usually is very fast, as it can typically be realized by computing a weighted linear combination of input channels.

No matter if supervised approaches like CSP, SPoC or other subspace methods shall be used for the analysis of multivariate brain signals, it usually is unclear a priori, in which exact task-related time segment and in which frequency band the informative oscillatory activity persists (Meinel et al., 2016b). While knowledge about these method- and task-specific hyperparameters would be desirable to have already at training time, it provides valuable insights also in the post-hoc analysis of experimental data collected during repeated executions or sessions of the task. For these reasons we present a method, that allows to characterize an oscillatory component in terms of its persistence over time and frequency space. We are convinced, that this characterization contributes valuable information which goes beyond a description of ERD/ERS behavior and of the spatial pattern.

2 METHODS

The decoding or even prediction of motor performance from brain signal recordings is a recent research topic (Meyer et al., 2014). In (Meinel et al., 2016a), we studied the sequential visual isometric pinch task (SVIPT, (Meinel et al., 2015)) as an example of a repetitive hand force task. While we refer the reader to (Meinel et al., 2015) for details on this hand force training task, it is helpful to know, that each repetitive trial required the user to control the horizontal movement trajectory of a cursor on the screen by applying varying levels of pinch force to sensor. Per trial, behavioral performance metrics such as the deviation from the optimal trajectory, reaction time after the trial start etc. were measured. For details on SVIPT metrics and correlations among different metrics please refer to (Tangermann et al., 2015). The EEG activity of participants was recorded prior and during the execution of SVIPT trials using $d = 63$ gel-based Ag/AgCl electrodes and BrainAmp amplifiers. Thriving to find an explanation for the observed strong inter-trial variability of the motor performance, we were able to identify robust pre-trial oscillatory components, i.e. components whose band power was informative to predict the single-trial motor performance. For a discussion on robustness scores please refer to (Castaño-Candamil et al., 2015). Based on the multichannel EEG recordings, spatial filters and resulting oscillatory components were computed with SPoC using trial-wise continuous performance labels z. More precisely, the spatial filters were trained using one epoch of EEG data per trial, which was extracted as a 750 ms wide time segment. The segment's position within the trial is described by the hyperparameter t_{train}, which marks the end of the segment. In addition, the data were filtered prior to the training of the spatial filter method to a passband of 1.5 Hz width around a central frequency f_{train} of this band. For SPoC training, epochs of the EEG had been extracted from trial-wise time segments located just before the go-cue ($t_{train} = -50ms$).

For this short paper, we selected a single, representative spatial filter derived by SPoC, which was trained on data of the beta frequency band $f_{train} = 28.8$ Hz and used the trial-wise reaction time as label z. In Fig. 1A, we show an example of a derived spatial filter $w_{train} \in \mathbb{R}^d$. The Figure shows the filter together with the corresponding spatial pattern. For information on the relation between filters and patterns in spatial subspace decomposition methods we refer the reader to (Haufe et al., 2014).

To obtain an estimate of the label z_{est} for a novel data epoch e, the trained spatial filter $\mathbf{w}_{train}$ is applied to the spatial covariance estimate $\Sigma(e,t,f)$ of the data epoch:

$$z_{est}(e) = \mathbf{w}_{train}^T \, \Sigma(e,t,f) \, \mathbf{w}_{train} \quad (1)$$

Please note, that the covariance estimate requires to make an explicit choice of the hyperparameters (t, f).

Equation 1 now allows to test the persistence of a given oscillatory component on the **same** data set. Therefore we evaluated the estimated labels z_{est} according to Equation 1 with $N = 500$ novel, randomly chosen time-frequency hyperparameter pairs (t_{test}, f_{test}) within the frequency range of 1 to 46 Hz and for time segment endpoints within -2.5 s to +2.0 s relative to the go-cue of each SVIPT trial.

For characterizing the sensitivity of the component with respect to varying hyperparameters the z-AUC performance is reported. Related to the area under the receiver-operator characteristics curve (AUC), the z-AUC describes how well the estimated labels z_{est} gathered by the band power of the SPoC component are in accordance with the measured trial-wise motor performance labels z. We decided to use z-AUC rather than the correlation coefficient r as an evaluation score for the component's persistance, as it has shown to be less sensitive to varying training set size. For further details see (Meinel et al., 2016a).

The interpolation and visualization of z-AUC resulting from various hyperparameter pairs was performed using using functional ANOVA toolbox (Hutter et al., 2014).

3 RESULTS

An exemplary oscillatory component derived by SPoC is characterized in Fig. 1A by the spatial filter and pattern of the component. Its band power was found to predict the trial-wise SVIPT reaction time. The pattern could be interpreted such, that the component reflects the status of the motor system.

As shown in Fig. 1B, its persistence has been tested for many hyperparameter pairs, which go beyond the frequency of 28.8 Hz and the temporal segment of [-800 -50] ms relative to the go-cue, on which the component had been trained. It can be observed, that the component is able to extract information about the task performance (reaction time in this example) also in time intervals after the go-cue. This information subsides at around 800 ms after the go cue, which is not unexpected, as most of the motor reactions already have happened at this latency. Interestingly, a second informative time interval around 1.5 s after the go cue is observed, which may be caused by the repetitive structure within each single SVIPT trial.

The information extracted by the component is visible in a large beta band (approximately in the range of 15 to 35 Hz and also in the the gamma band above 35 Hz. In this gamma band, however, the informative time intervals are shorter than in the beta band. Interestingly, these frequency ranges and time interval, i.e. the existance range of the component, by large extends the original parameters (t_{train}, f_{train}) that have been used to extract the component with SPoC.

4 DISCUSSION

In previous work with SPoC on data derived with the SVIPT hand motor training, we had identified a number of oscillatory components, which allowed to predict trial-wise SVIPT reaction time (and other performance metrics). We reported these components in (Meinel et al., 2016a), but have not yet described a method to characterize their stability in the time-frequency domain.

Based upon an oscillatory EEG component that has the ability to predict or decode behavioral performance, we have introduced a method, which allows to describe how the task-related information of this component persists over time and in frequency space. We have evaluated the method for an exemplary component which had been found in our earlier study. The method will open the door for an re-analysis of large collections of informative components and may in the future contribute to their functional interpretation.

A similar sensitivity analysis termed *event-related spectral pertubation analysis* has recently been proposed by Mousavi and colleagues for a motor imagery BCI paradigm. Comparing class-informative information in the oscillatory domain along the time-frequency space (Mousavi et al., 2017), their approach involves multiple training repetitions of the CSP spatial filtering method, while our proposed method requires evaluations of a trained component only, but does not require full re-training for every hyperparameter pair.

The in-depth characterization of components with our method clearly goes beyond a description based on solely the ERD/ERS behavior or the corresponding spatial patterns. While applied exemplarily to a SPoC component, the proposed method is not restricted to SPoC and can be utilized to characterize any type of spatial filter / component.

We propose to use a component's persistence in the time- and frequency domain in order to track changes over sessions and we argue that this is useful in various scenarios. Examples are cognitive and memory tasks (Klimesch, 1999), when changes of oscillatory activity is induced by motor learning in sports, or over the course of BCI-supported motor rehabilitation after stroke — a field which recently received a lot of attention (Soekadar et al., 2015; Remsik et al., 2016). In experimental scenarios with a restricted, similar functional context, this form of analysis may even help to identify corresponding oscillatory components across users and can thus support novel forms of group level analyses.

ACKNOWLEDGEMENTS

The authors are thankful for support by the Cluster of Excellence BrainLinks-BrainTools, funded by the German Research Foundation (DFG, grant number EXC 1086) and by state of Baden-Württemberg through bwHPC and the German Research Foundation (DFG) through grant no INST 39/963-1 FUGG. Finally, we want to thank Katharina Eggensperger and Frank Hutter for providing software on the hyperparameter analysis.

REFERENCES

Castaño-Candamil, J. S., Meinel, A., Dähne, S., and Tangermann, M. (2015). Probing meaningfulness of oscillatory EEG components with bootstrapping, label noise and reduced training sets. In *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*, pages 5159–5162. IEEE.

Dähne, S., Meinecke, F. C., Haufe, S., Höhne, J., Tangermann, M., Müller, K.-R., and Nikulin, V. V. (2014). SPoC: a novel framework for relating the amplitude of neuronal oscillations to behaviorally relevant parameters. *NeuroImage*, 86(0):111–122.

Fukunaga, K. (1990). *Introduction to statistical pattern recognition (2nd ed.)*. Academic Press Professional, Inc., San Diego, CA, USA.

Haufe, S., Meinecke, F., Görgen, K., Dähne, S., Haynes, J.-D., Blankertz, B., and Biemann, F. (2014). On the interpretation of weight vectors of linear models in multivariate neuroimaging. *NeuroImage*, 87(0):96 – 110.

Höhne, J., Holz, E., Staiger-Sälzer, P., Müller, K.-R., Kübler, A., and Tangermann, M. (2014). Motor imagery for severely motor-impaired patients: Evidence for brain-computer interfacing as superior control solution. *PLoS ONE*, 9(8):e104854.

Hutter, F., Hoos, H., and Leyton-Brown, K. (2014). An efficient approach for assessing hyperparameter importance. In *Proceedings of International Conference on Machine Learning 2014 (ICML 2014)*, pages 754–762.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Research Reviews*, 29(2):169–195.

Koles, Z. J. (1991). The quantitative extraction and topographic mapping of the abnormal components in the clinical EEG. *Electroencephalography and clinical Neurophysiology*, 79(6):440–447.

Lotte, F. and Guan, C. (2011). Regularizing common spatial patterns to improve BCI designs: unified theory and new algorithms. *IEEE Transactions on Biomedical Engineering*, 58(2):355–362.

Meinel, A., Castaño-Candamil, S., Reis, J., and Tangermann, M. (2016a). Pre-trial EEG-based single-trial motor performance prediction to enhance neuroergonomics for a hand force task. *Frontiers in Human Neuroscience*, 10:170.

Meinel, A., Castao-Candamil, J. S., Dähne, S., Reis, J., and Tangermann, M. (2015). EEG band power predicts single-trial reaction time in a hand motor task. In *Proc. Int. IEEE Conf. on Neural Eng. (NER)*, pages 182–185, Montpellier, France. IEEE.

Meinel, A., Eggensperger, K., Tangermann, M., and Hutter, F. (2016b). Hyperparameter optimization for machine learning problems in BCI. In Müller-Putz, G., Huggins, J., and Steyrl, D., editors, *Proceedings of the 6th International Brain-Computer Interface Meeting: BCI Past, Present, and Future*, page 184, Asilomar Conference Center, Pacific Grove, California, USA. Verlag der Technischen Universität Graz.

Meyer, T., Peters, J., Zander, T. O., Schölkopf, B., and Grosse-Wentrup, M. (2014). Predicting motor learning performance from electroencephalographic data. *Journal of Neuroengineering and Rehabilitation*, 11(1):24.

Mousavi, M., Koerner, A. S., Zhang, Q., Noh, E., and de Sa, V. R. (2017). Improving motor imagery BCI with user response to feedback. *Brain-Computer Interfaces*, 4(1-2):74–86.

Müller, K.-R., Tangermann, M., Dornhege, G., Krauledat, M., Curio, G., and Blankertz, B. (2008). Machine learning for real-time single-trial EEG-analysis: From brain-computer interfacing to mental state monitoring. *Journal of Neuroscience Methods*, 167(1):82–90.

Pfutscheller, G., Neuper, C., Flotzinger, D., and Pregenzer, M. (1997). EEG-based discrimination between imagination of right and left hand movement. *Electroencephalography and Clinical Neurophysiology*, 103:642–651.

Ramoser, H., Müller-Gerking, J., and Pfurtscheller, G. (2000). Optimal spatial filtering of single trial EEG during imagined hand movement. *Rehabilitation Engineering, IEEE Transactions on*, 8(4):441–446.

Remsik, A., Young, B., Vermilyea, R., Kiekhoefer, L., Abrams, J., Evander Elmore, S., Schultz, P., Nair, V., Edwards, D., Williams, J., et al. (2016). A review of the progression and future implications of brain-computer interface therapies for restoration of distal upper extremity motor function after stroke. *Expert Review of Medical Devices*, 13(5):445–454.

Soekadar, S. R., Silvoni, S., Cohen, L. G., and Birbaumer, N. (2015). Brain–machine interfaces in stroke neurorehabilitation. In *Clinical Systems Neuroscience*, pages 3–14. Springer.

Tangermann, M., Müller, K.-R., Aertsen, A., Birbaumer, N., Braun, C., Brunner, C., Leeb, R., Mehring, C., Miller, K., Müller-Putz, G., Nolte, G., Pfurtscheller, G., Preissl, H., Schalk, G., Schlögl, A., Vidaurre, C., Waldert, S., and Blankertz, B. (2012). Review of the BCI competition IV. *Frontiers in Neuroscience*, 6(55).

Tangermann, M., Reis, J., and Meinel, A. (2015). Commonalities of motor performance metrics are revealed by predictive oscillatory EEG components. In *Proceedings of the 3rd International Congress on Neurotechnology, Electronics and Informatics (NEUROTECHNIX)*, pages 32–38, Lissabon.

van Erp, J., Lotte, F., and Tangermann, M. (2012). Brain-computer interfaces for non-medical applications: How to move forward. *Computer*, pages 26–34.

Wolpaw, J. R. and Wolpaw, E. W., editors (2012). *Brain-computer interfaces : principles and practice*. Oxford University press. ISBN-13: 978-0195388855.