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GUEST EDITORIAL

Progress in EEG: Multi-subject Decomposition and Other Advanced Signal Processing Approaches

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Electroencephalography (EEG) is generally considered a well-established technique that has extensively been applied to study brain function in health and disease. EEG has been tremendously successful in shaping our understanding of the building blocks of cognition, and how those differ across experimental contexts or between groups of individuals. One major obstacle in the interpretation of EEG, however, is its notoriously low spatial resolution. Electrical currents caused by a multitude of synchronously active neural generators travel through the brain, guided by local conductivity differences of the tissue, pass the skull and finally are registered at relatively wide-spaced electrodes attached to the skin. Care has to be taken when interpreting certain phenomena at selected electrodes across subjects, because already minor differences in brain morphology or generator constellations can obscure or bias actual neural differences (or the lack thereof). Inverse modeling of EEG thus tries to trace the electric potentials measured at the surface of the scalp back to their origins within the brain. To solve this ill-posed problem, a number of mathematical constraints have to be introduced that may (to a certain degree) be derived from the physical characteristics of neural generators and current flows. EEG inverse modeling in itself is an established and active research field, yet one of its major limitations is its predominant reliance on the relatively sparse spatial information of EEG. More recent procedures, largely driven by machine learning applications to neuroscience data, instead exploit the much richer information found in EEG's temporal domain. Algorithms for blind source separation, such as independent component analysis (ICA), try to decompose the manifest EEG recordings into its constituent source signals, which then correspond to activity patterns of single regions or coherent neural networks. These techniques are often applied to the data of single subjects. Most EEG researchers will have used ICA for the removal of eye activity, for example, but a growing number of studies use these decompositions to study the latent structure of EEG itself. Methods for the group-level decomposition of EEG data, thus techniques that directly infer the latent structure common across data sets of multiple subjects, are tailored towards solving this exact problem. In functional magnetic resonance imaging, techniques for group-level or multi-subject decomposition have been extremely successful for the study of brain networks and their dynamics at rest or during cognitively demanding tasks, in both healthy as well as clinical populations. Their adaptation and application to EEG data, also extremely powerful and promising, constitutes a rather recent development and is the topic of this collection of articles.

This special issue highlights work on both the technical aspects as well as the application of techniques for multi-subject data decomposition of EEG data. Our major aim is to stimulate this field by encouraging and supporting researchers to apply these techniques even though they may not consider themselves methodological experts, while likewise providing more specialist knowledge to interested methodologists to advance the algorithmic development. But the field has meanwhile also advanced with respect to many other techniques for EEG signal processing, and we would like to take the opportunity to highlight some of these as well.

The first contribution by Huster and Raud (2017) specifically targets researchers with only limited experience in

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advanced EEG processing. This tutorial-review introduces the concepts behind main approaches to multi-subject data decomposition as applied to EEG, and further elucidates some of the potential pitfalls that need special consideration when choosing the best-suited approach. Evoked, induced, or resting activity, for example, require different methodological twists, and the tutorial-review seeks to guide researchers through the most important choices.

The following two articles showcase how multi-subject data decomposition can aid the analysis of EEG obtained from complex cognitive tasks. Both studies, Enriquez-Geppert et al. and van Dinteren et al., assess aging-related trajectories of the P300 in different tasks, that is in task-switching and an auditory oddball task, respectively. These studies report significant age-related changes in P300 topographies from early to late adulthood, with the latter exhibiting a shift of activity towards frontal electrodes. Such topographical differences suggest changes in the underlying generator constellation, and usually hinder an integrative interpretation of these phenomena across age-groups. By concurrently decomposing the data of different age-groups one inherently matches temporal activity patterns across subjects while preserving topographical differences. This allows the authors to study and compare common neural phenomena with different expressions across subject groups.

The next two papers focus on the algorithmic side of multi-subject decomposition. Bridwell et al. compare the performance of twelve different algorithms for blind source separation in context of spatiospectral multi-subject EEG decomposition. The algorithms were tested on both simulated and real data, and the stabilities of the solutions were compared. Somewhat surprisingly perhaps, the algorithms exhibit substantial performance differences, an observation that needs to be followed up in future work. Lio and Boulinguez then propose a framework to use UWSOBI on multi-subject data in the temporal domain and compare it to temporal concatenation group ICA, while systematically varying the projection of brain sources to scalp electrodes across subjects. Temporal group UWSOBI overall shows good performance and robustness against topographical variability, yet performance is not optimal with temporal concatenation group ICA.

Reproducibility and generalizability of decompositions are important yet often overlooked aspects, as addressed in this issue by Labounek et al. and Wessel. Labounek et al. compared the decompositions of EEG data recorded at rest, when subjects performed a semantic decision task, as well as during a visual oddball task. Of the 20 spatiospectral components extracted for each of the 3 states, 14 components were found to reproduce and generalize across the different recording contexts. Wessel then discusses the consequences of such findings, i.e. the observation that certain components can be found to be active in different conditions of a single task, as well as across different tasks or mental states. He then outlines how this observation can be used to test neural theories of mental functions.

The final four contributions to this special issue provide a broader perspective on advanced analytic approaches. Allen et al. present an analysis that binds spectral EEG features to fMRI components, and further shows how functional connectivity patterns dynamically change, not only across different recording settings (e.g., at rest with eyes open vs. eyes closed), but also within a single recording context. Emge et al. present a novel way to apply independent vector analysis to improve the detection of steady-state visual evoked potentials as recorded under different stimulation protocols and across subjects. The authors then discuss the implications of their findings for both basic and applied neuroscientific research. Dinh et al. also introduce a modified version of a successful and well-established technique, namely real-time clustered multiple signal classification. This application is optimized for a real-time source localization that they argue can withstand low signal-to-noise ratios and can operate at low computational demands. Finally, Steyrl et al. present a new online approach for the removal of artifacts in simultaneous EEG–fMRI acquisition settings. They combine an average artifact subtraction (AAS) method with reference recordings of artifacts from a prototype electrode cap alongside adaptive filtering. Steyrl et al. provide evidence that reference layer adaptive filtering combined with AAS improves artifact reduction relative to established offline methods.

We hope that this collection of articles will help to further spread and support the application of multi-subject data decomposition and other advanced singal processing techniques for EEG.