Estimating Target Orientations: A Comparison of Beamformer Algorithms and their Performances in Estimating Orientations of Neural Sources

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***Abstract*—The efficacy of transcranial electric stimulation (TES) to modulate neuronal activity depends critically on the spatial orientation of the targeted neuronal population. Therefore, precise estimation of the target orientation is of utmost importance. Different beamforming algorithms provide orientation estimates, however, a systematic analysis of their performance is still lacking.**

For a fixed brain location, EEG and MEG data from sources with randomized orientations are simulated. The orientation is then estimated (1) with an EEG and (2) with a combined EEG-MEG approach. Three commonly used beamformer algorithms are evaluated: Unit-Gain (UG), Unit-Noise-Gain (UNG), Array-Gain (AG).

Differences between the beamformers' abilities to estimate the correct orientation are shown. Performance depends on the ratio of radial and tangential components of the orientation and on noise levels. This study is a first step towards establishing best practice for source orientation estimation, further investigation is needed.

***Index Terms*—beamforming, orientation, electroencephalography, magnetoencephalography, personalized TES**

I. INTRODUCTION

In order to maximize the effects induced by transcranial electric stimulation, determining the orientation of the targeted neuronal population is crucial [3],[5]. Beamformer algorithms provide the possibility to estimate these orientations from recorded MEG and EEG data as directions with maximum power [6]. However, a systematic evaluation of their performance is still lacking, leaving researchers with a difficult choice of which algorithm to apply. This study attempts to fill this gap by testing the performance of three commonly used beamformer algorithms. A simulation study is performed, where known orientations are estimated. Performances of the algorithms and different modalities (EEG and combined EEG and MEG) are analyzed.

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II. METHODS

This study compares the Unit-Gain (UG), the Unit-Noise-Gain (UNG) and the Array-Gain (AG) Beamformers, which are described in [6] and implemented in fieldtrip [4]. All three beamformers offer algorithms to optimize the source orientation, which depend on the target leadfield, the covariance matrix of the EEG- or MEG-data and regularization parameters.

For one exemplary subject, a realistic stimulation target location in area V5 was identified based on fMRI activity during an occulomotor task. Leadfields were computed based on realistic Finite Element headmodels as described in [1]. EEG and MEG signals of a sinusoidal source at V5 (60 seconds, 600 Hz sampling frequency) were simulated and Gaussian noise of different levels was added before computing the covariance matrices.

For EEG, the orientation in all three spatial directions is estimated. For the combined EMEG estimations, it is assumed that the EEG is superior in estimating the component, which is radially oriented to the skull [2]. In contrast, MEG is assumed to be more precise in estimating the tangential components.

To combine these estimates, the target leadfield of the MEG is decomposed with a Singular Value Decomposition. The singular vector corresponding to the lowest singular value is interpreted as the radial direction, while the other two vectors are considered the tangential components. The combined estimate results from the superposition of the tangential component as obtained by MEG and the radial component as obtained by EEG. Regularization parameters were kept at 0.05 for both modalities.

In the first part of the study, datasets of 1000 randomly generated orientations were simulated. The angle between the real and the estimated orientation serves as a measure of performance.

In the next part of the study, orientations were created systematically to sample the entire sphere of possible orientations. Using bootstrapping, each orientation was estimated 200 times, computing covariance matrices from random time bins of the simulated data. The median angle was extracted across the bootstrapped estimates for each of the simulated orientations.

To determine, which estimation is closer to the original orientation, EEG or combined EMEG, the difference between the estimates of the two modalities is computed.

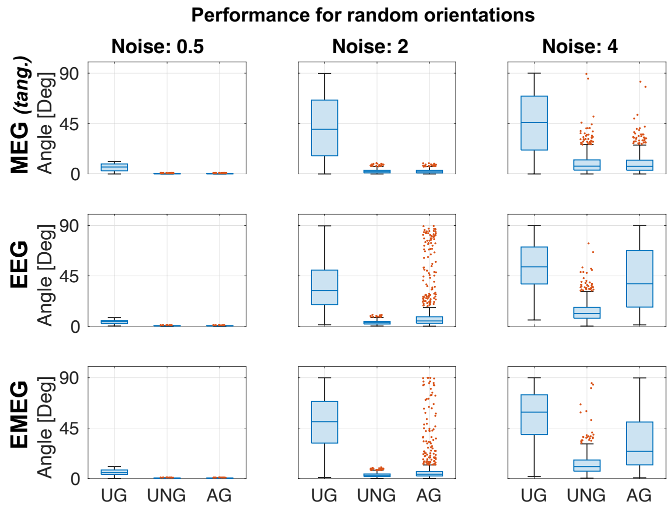

Fig. 1: Angle between original and estimate for 1000 randomly generated orientations for different algorithms, noise levels and modalities.

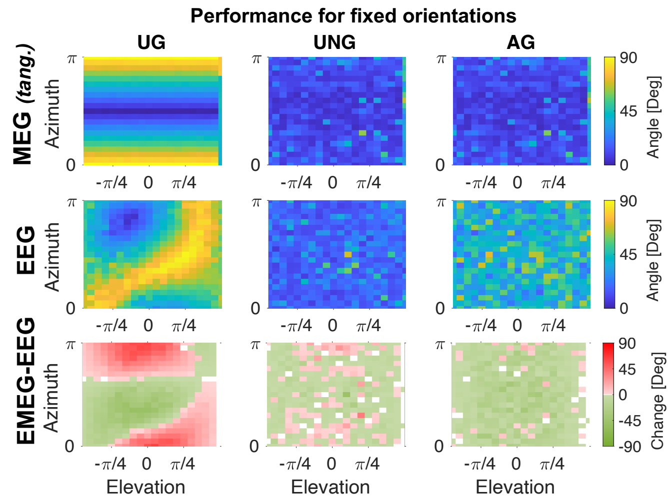

Fig. 2: Beamformer performance for MEG (upper) and EEG (middle) for fixed orientations at noise level 4. Difference between EMEG- and EEG-estimation (lower). All orientations are displayed in spherical coordinates.

III. Results

We found that the tested beamformer algorithms lead to different estimations of the same orientation. Therefore, the range of deviation from the original orientation varies strongly. As can be seen in Fig. 1, the performance of UNG and AG is similar in MEG, but the UNG algorithm outperforms the other two in EEG and EMEG in all noise levels. The performance of the combined EMEG approach is slightly better than the one of the pure EEG, which confirms our expectations.
Figure 2 displays the angle between estimated and original orientation for fixed orientations. For the UG beamformer, a directionality was found, meaning that its performance depends strongly on the orientations to be estimated. For the UNG and AG no such dependence was found. It is furthermore visible, that for UNG and AG, most estimates are improved by using the combined analysis. For the UG however, using the combined EMEG analysis, strongly improves or deteriorates the estimate depending on the orientation. Coherent with this finding it was evaluated that from a certain noise level, the UG maps all orientations to the singular vector corresponding to the lowest singular value of the leadfield (not visualized here). Similar results were found for different subjects, targets and source waveforms.

IV. Conclusion

This study shows, that estimating target orientations from beamformer algorithms should be done with great care. The performance of the algorithm depends on the noise level of the data and on the orientations of the underlying source. Overall, the study implies, that UNG is the best beamformer to estimate orientations. The second part of the study shows, that for UNG and AG, most estimates are improved when using the combined analysis. Although some estimates deteriorate, combining EEG and MEG should still be considered. The most obvious reason is the noise level, which has not been varied independently between EEG and MEG. In real data, the noise levels between EEG and MEG can differ strongly and including MEG estimates will be especially advantageous, when noise in MEG is less strong than in EEG. Further limitations comprise the noise approximation with Gaussian noise and the single target location, which holds only limited information about the estimation of target orientations in other brain regions.

Acknowledgments

This work was supported by the Deutsche Forschungsgemeinschaft (DFG), projects WO1425/10-1, GR2024/8-1 and LE1122/7-1 and by the Bundesministerium für Gesundheit (BMG) as project ZMI1-2521FSB006, under the frame of ERA PerMed as project ERAPERMED2020-227. We thank Andreas Wollbrink for technical assistance and Karin Wilken, Hildegard Deitermann and Ute Trompeter for their help with the EEG/MEG/MRI data collection.

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