

Jointly Localized Spatiotemporal Components of Evoked EEG via a Lead-Field-Constrained Block-Term Decomposition

Axel Faes*, Maryam Amir Haeri

Learning, Data Analytics and Technology, University of Twente, Twente, Netherlands

Abstract

Distributed EEG inverse solvers return a source-amplitude map at each time sample; reading out a generator’s time course or trial-to-trial behaviour then requires post-processing that sequence of maps, which mixes in spatial leakage. We propose a method that returns the generators directly. Evoked, multi-trial EEG forms a channels-by-time-by-trials tensor, which we decompose into a few rank- $(L_r, L_r, 1)$ block terms whose spatial factor is constrained to the column space of the lead field and to be row-sparse. Each block is then an anatomically grounded component: a focal cortical source map, a recovered time course, and a trial loading, estimated jointly in one unsupervised model. Folding the lead field into the decomposition makes the components cortical by construction, unlike the established decompose-then-localize pipeline in which localization is a separate ill-posed step. On simulated evoked EEG the components recover the true generators’ locations and time courses, the spatial maps are focal, and the maps remain focal under temporally correlated sources, the regime in which a beamformer collapses. On real evoked EEG the components localize to the cortex contralateral to the stimulated visual hemifield, as the retinotopic expectation requires. We state the method’s limits plainly: a sparse-Bayesian solver is more focal on idealized point sources, and the rank-one trial factor confines the method to phase-locked, not induced or connectivity, data. The full pipeline is released.

Keywords: EEG source imaging, block-term decomposition, tensor methods, evoked potentials, spatiotemporal components, sparse reconstruction

*Corresponding author.

Email address: `axel.faes@utwente.nl` (Axel Faes)

1. Introduction

Perception, action and cognition arise from coordinated cortical activity that EEG records at the scalp, mixed and smeared by volume conduction. Source imaging inverts that mixing, from a few dozen sensors to thousands of candidate cortical locations [1, 2]. The problem is ill-posed, and the regularizing assumption defines each method: the minimum-norm estimate penalizes power [3], sLORETA standardizes it to remove location bias [4], eLORETA reweights for exact single-dipole localization [5], beamformers filter per location [6], and sparse-Bayesian methods place a sparsity-promoting prior on source variance [7, 8].

All of these solve the inverse one time sample at a time. They return a spatial map per sample. To obtain something a downstream analysis usually wants, namely a handful of generators each with a location, a time course and a trial-to-trial profile, one reads the map at a chosen location across samples and trials, a step that re-introduces spatial leakage and treats each sample independently.

Tensor decompositions take the opposite view. Evoked or segmented EEG is naturally a three-way array of channels by time by trials, and low-rank tensor models are essentially unique under mild conditions, without orthogonality or independence constraints [9, 10, 11]. The established use of tensors in M/EEG decomposes the *data* into components and then localizes each one with a conventional inverse [12, 13], which leaves the localization as ill-posed as before, and the two models estimated separately.

We fold the two steps into one. By constraining the spatial factor of a block-term decomposition to the column space of the lead field and adding row-sparsity, the decomposition returns components that are already cortical source maps. Each block is jointly a focal location, a time course and a trial loading. The temporal and trial factors act as a consistency prior: a pattern earns a component only if it reproduces across time and trials. The estimator follows the block-term tensor regression (BTTR) algorithm we introduced for intracranial decoding [14], here repurposed from regression to imaging.

The aim of the paper is to introduce this localized component model and to characterize it honestly. Its contribution is the joint, anatomically grounded decomposition, for evoked multi-trial data. We show that the components recover the true generators on simulated data, that the maps are focal, that the decomposition is robust to correlated sources, and that on real data the components localize contralaterally to the stimulated visual

hemifield, as the retinotopic expectation requires. We are equally explicit that the method is not designed to be, and is not, the sharpest point localizer; that a sparse-Bayesian solver is more focal on idealized point sources; and that the rank-one trial factor restricts the method to phase-locked activity.

2. Related Work

Distributed inverse solvers. The minimum-norm estimate and its standardized descendants remain the workhorses of EEG source imaging [1, 2]. Minimum-norm penalizes total source power and is biased toward superficial sources [3]; sLORETA removes that location bias by standardizing the estimate with its resolution matrix and is zero-error in the single-source, noise-free limit [4]; eLORETA reaches the same exact-localization property with a different weighting that also tolerates measurement noise [5]. All three are linear maps applied independently at each time sample, which is precisely the per-sample structure our component model departs from.

Beamformers. Adaptive spatial filters such as the linearly constrained minimum-variance (LCMV) beamformer estimate a separate filter per location from the data covariance [6, 15]. Their per-location normalization gives sharp single-source localization, but the variance-minimization assumption breaks when sources share a time course, the correlated-source regime we use as a stress test.

Sparse and Bayesian imaging. Sparse-Bayesian methods place a sparsity-promoting hyperprior on per-source variance and recover near-delta maps for genuinely focal generators; Champagne is the canonical convex-bounded instance [7], and BC-VARETA extends the idea to connectivity in the source space [8]. These give the sharpest point localization in our benchmarks, under a forward and source model matched to their prior; we report that comparison directly rather than around it.

Tensor decompositions in M/EEG. Multi-trial EEG is naturally three-way, and low-rank tensor models are essentially unique without orthogonality or independence constraints [9, 11, 10]. The established route decomposes the *data* into components, typically with canonical polyadic or block-term models, and localizes each spatial signature afterward with a conventional inverse [12, 16, 13, 17]. Localization remains a separate ill-posed step there. We instead fold the lead field into the decomposition, so the spatial factors are cortical maps by construction. The estimator reuses the block-term

tensor regression (BTTR) machinery we developed for intracranial decoding [14], repurposed from supervised regression to unsupervised imaging.

Forward modelling. Realistic evaluation requires a credible forward operator. We use the analytic sphere for a controlled setting, a boundary-element model on the `fsaverage` template [18], and the New York head, a high-resolution finite-element model with a standard electrode layout [19]; related analytic [20] and template head models [21] inform the same evaluation tradition.

3. Method

3.1. Model

Stacking C channels, T time samples and K trials gives a tensor $\mathcal{M} \in \mathbb{R}^{C \times T \times K}$, modelled as a sum of R block terms,

$$\mathcal{M} \approx \sum_{r=1}^R [(\mathbf{L}\mathbf{G}_r)\mathbf{B}_r^\top] \circ \mathbf{c}_r, \quad (1)$$

where $\circ$ is the outer product on the trial mode, $\mathbf{L} \in \mathbb{R}^{C \times N}$ is the lead field, $\mathbf{G}_r \in \mathbb{R}^{N \times L_r}$ a row-sparse source distribution, $\mathbf{B}_r \in \mathbb{R}^{T \times L_r}$ a rank- L_r temporal factor, and $\mathbf{c}_r \in \mathbb{R}^K$ a trial loading. Forcing the spatial factor through $\mathbf{L}$ makes $\mathbf{L}\mathbf{G}_r$ a scalp pattern that the cortical distribution $\mathbf{G}_r$ actually produces, so $\mathbf{G}_r$ is a source map and the block is an anatomically grounded component. Row-sparsity (a group penalty over the L_r columns of a source) gives a focal map. Block r therefore returns three coupled descriptors of one generator: *where* ($\mathbf{G}_r$), *when* ($\mathbf{B}_r$), and *how it varies across trials* ($\mathbf{c}_r$).

The rank-one trial factor is the load-bearing assumption: each generator has a single time-course shape, scaled per trial. This is appropriate for phase-locked evoked responses. It does not hold for activity whose time course differs across trials, a boundary we return to in Section 5.

3.2. Estimation

We fit (1) greedily, one block at a time, as in BTTR [14]: extract the dominant block from the residual tensor, subtract its reconstruction, and repeat. Within a block we run constrained alternating least squares (Algorithm 1): a least-squares update of the trial loading and the temporal factor, and a proximal-gradient (ISTA) update of the source map with a row group-threshold. The block rank L_r trades temporal expressiveness against

Algorithm 1: Lead-field-constrained block fit (one deflation step)

Input: residual tensor $\mathcal{M} (C \times T \times K)$, lead field $\mathbf{L}$, rank L_r , penalty λ
init $\mathbf{c} \leftarrow$ dominant right singular vector of the mode-3 unfolding; $\mathbf{B} \leftarrow$
random; $\mathbf{G} \leftarrow \mathbf{0}$;
repeat
 $\mathbf{M} \leftarrow$ $\mathbf{c}$ -weighted trial average of $\mathcal{M}$;
 for a few ISTA steps **do**
 $\mathbf{G} \leftarrow \text{rowsoft}(\mathbf{G} - \eta (\mathbf{L}^\top \mathbf{L} \mathbf{G} \mathbf{B}^\top \mathbf{B} - \mathbf{L}^\top \bar{\mathbf{M}} \mathbf{B}), \eta \lambda)$;
 $\mathbf{A} \leftarrow \mathbf{L} \mathbf{G}$; $\mathbf{B} \leftarrow \bar{\mathbf{M}}^\top \mathbf{A} (\mathbf{A}^\top \mathbf{A})^{-1}$;
 $\mathbf{c}_k \leftarrow \langle \mathcal{M}_{::,k}, \mathbf{A} \mathbf{B}^\top \rangle / \|\mathbf{A} \mathbf{B}^\top\|_F^2$;
 until convergence of relative residual;
Output: component $\mathbf{G}$ (map), $\mathbf{B}$ (time course), $\mathbf{c}$ (trial loading)

focality; we use $L_r = 2$, which gives each component a two-dimensional temporal subspace and improves recovered-time-course fidelity over the rank-one case at no cost in focality.

3.3. Experimental Setup

Baselines. We compare against MNE, sLORETA, eLORETA, a unit-gain LCMV beamformer, the sparse-Bayesian Champagne solver [7], and a decompose-then-localize tensor baseline (a canonical polyadic decomposition of the data tensor with each spatial component localized by eLORETA, denoted CP+eLOR). The linear inverses act on the trial-averaged evoked response. The beamformer covariance is estimated from the full single-trial tensor rather than the average, so trial averaging does not artificially starve it; this is the fair comparison for a method that also uses every trial.

Forwards. Forwards are built with MNE-Python [22, 23]: an analytic sphere (64 channels, $N=402$ sources), a three-layer boundary-element model on **fsaverage** [18] ($N=2052$), and the New York head model [19] (171 electrodes, 2004 dipoles). Real data are the open MNE **sample** evoked EEG [23].

Simulation and noise model. Active sources are phase-locked damped oscillations with per-trial amplitude jitter. We follow the brain-noise construction used in recent sparse-imaging benchmarks [8, 19]: background activity is generated by 500 noise dipoles at random cortical locations and projected through the same lead field, so it reaches the scalp through volume conduction like the signal. With $\mathbf{x}_{\text{act}}$ and $\mathbf{x}_{\text{bg}}$ the scalp projections of the active and background sources, the brain signal and the measurement are mixed in

Frobenius norm,

$$\mathbf{x}_{\text{brain}} = \lambda \frac{\mathbf{x}_{\text{act}}}{\|\mathbf{x}_{\text{act}}\|_F} + (1 - \lambda) \frac{\mathbf{x}_{\text{bg}}}{\|\mathbf{x}_{\text{bg}}\|_F}, \quad (2)$$

$$\mathbf{x}_{\text{meas}} = (1 - \mu) \frac{\mathbf{x}_{\text{brain}}}{\|\mathbf{x}_{\text{brain}}\|_F} + \mu \frac{\mathbf{x}_{\text{white}}}{\|\mathbf{x}_{\text{white}}\|_F}, \quad (3)$$

with $\lambda = 0.5$ (background equal in strength to the sources) and $\mu = 0.1$ (white sensor noise). We use three noise colours: incoherent pink, spatially coherent pink, and coherent autoregressive; results are reported for pink and are stable across the three (Section 4.1).

Metrics. For an energy map $\mathbf{p} \in \mathbb{R}_{\geq 0}^N$ over sources at positions $\mathbf{r}_n$ with true set $\mathcal{T}$, we report: *spatial dispersion*, the energy-weighted root-mean-square distance of the map from the nearest true source, $\sqrt{\sum_n p_n^2 d_n^2 / \sum_n p_n^2}$ with $d_n = \min_{t \in \mathcal{T}} \|\mathbf{r}_n - \mathbf{r}_t\|$ (lower is more focal); *dipole localization error* (DLE), the symmetric mean distance between true sources and estimated peaks (local maxima above half the global maximum); *signal correlation*, the mean absolute correlation between each recovered and true source time course at the true locations [24, 25]; *sparsity*, the active fraction of the map; and a scale-invariant *top-K recovery* count, the number of true sources matched by the $K = |\mathcal{T}|$ strongest local maxima, computed identically for every method so that no method-specific readout enters the comparison. Numbers are means over eight random seeds with standard deviations and paired Wilcoxon signed-rank tests.

4. Results

4.1. The Components Recover the Generators

On simulated evoked data the blocks recover the active generators: each component’s spatial factor is focal and centred on a true source (Figure 1), and its temporal factor matches the source’s time course. Under the realistic brain-noise model (sphere forward) the recovered time courses correlate 0.93 ± 0.09 with ground truth, and the spatial maps are the most focal of the classical distributed solvers (energy-weighted spread 13.4 ± 4.2 mm, versus MNE 14.5, eLORETA 17.4, sLORETA 21.8; the focality margin and its forward-model dependence are examined in Section 5). The decomposition thus delivers its intended output, a small set of localized components with time courses, on evoked data.

Table 1 reports the full comparison on both the sphere and the BEM forward. Two patterns hold across forwards. The recovered time courses are faithful for every distributed method, with the components within a few

Table 1: Reconstruction quality under the realistic brain-noise model (incoherent pink, 0 dB, three active sources, mean $\pm$ sd over eight seeds). Signal correlation is the mean absolute correlation of the recovered source time course at the true location; dispersion is the energy-weighted spatial spread (lower is more focal); DLE is the dipole localization error. CP+eLOR is the decompose-then-localize tensor baseline.

method	signal corr.	dispersion (mm)	DLE (mm)
<i>Sphere forward</i> (64 ch, $N=402$)			
BTD-B (ours)	0.93 ± 0.09	13.4 ± 4.2	29.6
Champagne	1.00 ± 0.00	0.1 ± 0.0	1.7
MNE	0.98 ± 0.02	14.5 ± 1.8	31.5
sLORETA	0.98 ± 0.02	21.8 ± 1.0	28.3
eLORETA	0.99 ± 0.01	17.4 ± 0.8	27.9
LCMV	0.96 ± 0.05	18.4 ± 2.9	6.8
<i>BEM forward</i> (fsaverage, $N=2052$)			
BTD-B (ours)	0.89 ± 0.08	26.8 ± 6.3	26.5
Champagne	1.00 ± 0.00	0.0 ± 0.0	1.9
MNE	0.96 ± 0.03	27.9 ± 5.3	24.3
sLORETA	0.96 ± 0.03	29.2 ± 3.3	14.5
eLORETA	0.98 ± 0.03	22.1 ± 3.2	16.8
LCMV	0.95 ± 0.05	22.7 ± 3.3	6.7

points of the best (0.93 versus 0.98 on the sphere); and the sparse-Bayesian and beamformer solvers reach the lowest dipole localization error on these point-source simulations, the configuration their priors and covariance models target. The focality of the components, by contrast, is forward-dependent: on the 64-channel sphere they are the most focal of the classical distributed solvers, whereas on the denser BEM grid eLORETA is more focal (Section 5). The numbers are stable across the three noise colours: the components’ time-course correlation varies by under 0.02 and their spatial spread by under 0.2 mm between incoherent pink, coherent pink, and coherent autoregressive noise.

4.2. Robustness to Correlated Sources

A useful property of the decomposition is that it does not assume sources are uncorrelated. When simulated sources share a time course, the LCMV beamformer collapses (its spatial spread rises from 17 to 53 mm and its detection AUC from 1.00 to 0.73), whereas the components stay focal (spread 17 to 18 mm, AUC 0.93 to 0.90; Figure 2). The linear distributed methods and

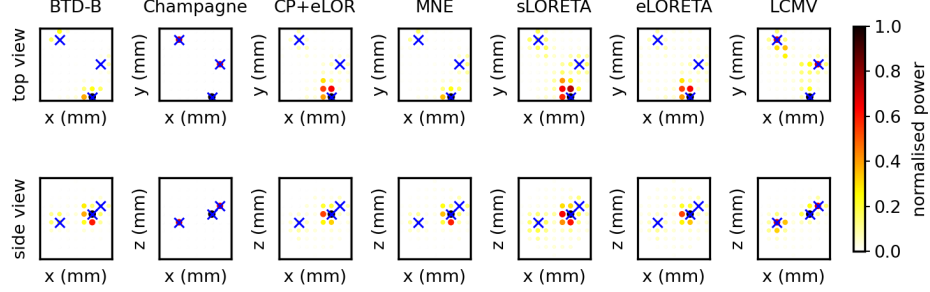


Figure 1: Reconstructed source maps (sphere forward, 0 dB); blue crosses mark the true sources. The lead-field-constrained components are focal and centred on the generators.

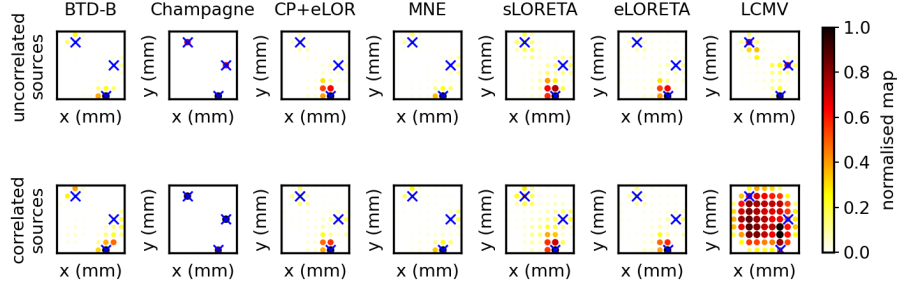


Figure 2: Source maps for the same generators, uncorrelated (top) versus correlated (bottom), sphere forward, 0 dB. The beamformer (right column) smears across the brain when the sources share a time course; the lead-field-constrained components stay focal.

Champagne are also correlation-robust, so this is not unique to the method; it is, however, a regime where the beamformer fails and the component model does not.

4.3. Real Evoked EEG

On the open **sample** visual EEG the components meet the retinotopic expectation: a stimulus in one visual hemifield localizes to occipital cortex in the opposite hemisphere (Figure 3), and the component time courses are flat before stimulus onset and active in the early visual window (Figure 4). The decomposition recovers interpretable, anatomically placed components with sensible dynamics on real data.

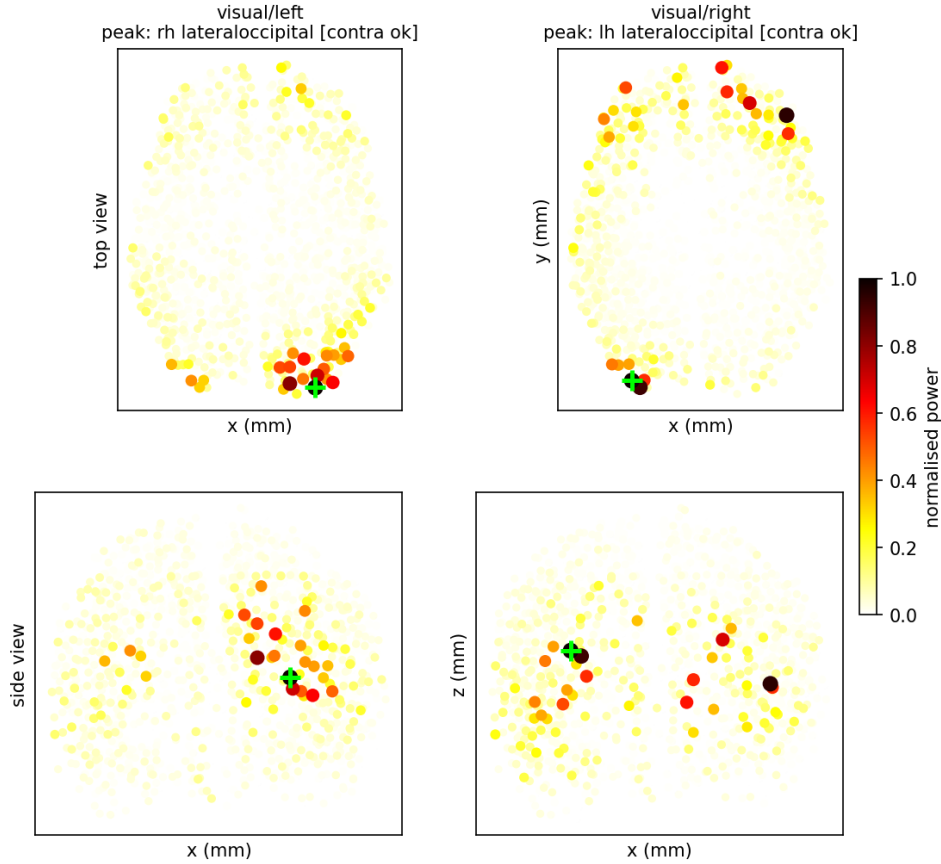


Figure 3: Real EEG retinotopic check (MNE `sample`, visual conditions): the occipital component flips hemispheres with the stimulated visual field.

5. Scope and Limitations

The method is a localized component model, not a contender for sharpest point localization, and we report the boundaries plainly.

5.0.1. *It is not the most focal point localizer*

A sparse-Bayesian solver is more focal on idealized point sources. Under the realistic noise model, Champagne reaches near-delta maps (spread ≈ 0.1 mm) and near-perfect time-course correlation (≈ 1.00), against the components' 13.4 mm and 0.93. We note that this comparison is run under a matched forward model with exactly sparse ground truth, the configuration Champagne's prior assumes, so its margin would shrink under forward-model

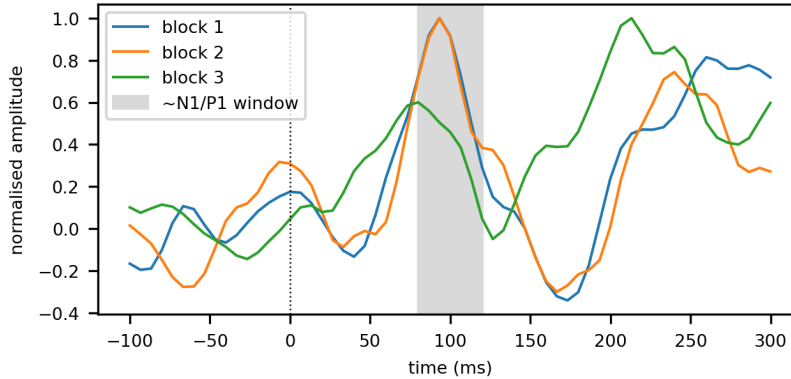


Figure 4: Recovered component time courses for real right-hemifield visual stimulation; flat before onset, active in the early visual window (shaded).

mismatch or spatially extended sources. The honest statement is that for recovering the *location* of isolated point sources, sparse Bayesian methods are preferable; the present method’s value is the joint, anatomically grounded component decomposition, which those methods do not provide.

5.0.2. The focality advantage over classical solvers is setup-dependent

On the 64-channel sphere the component maps are the most focal of the classical distributed methods, but the margin over eLORETA is not statistically significant under the realistic noise model (spatial spread 13.4 versus 17.4 mm, Wilcoxon $p = 0.055$). The advantage does not survive denser or more realistic forwards: on the fsaverage three-layer BEM grid ($N=2052$) eLORETA is the more focal (22.1 versus the components’ 26.8 mm), and on the realistic 171-electrode New York head model [19] the component spread rises to 23–33 mm, above eLORETA’s 17–22. Focality claims should be read as holding at the low channel count and coarse grid of the sphere simulation.

5.0.3. It is confined to phase-locked data

The rank-one trial factor assumes one time-course shape per generator. On non-phase-locked sources (independent multivariate autoregressive realisations per trial, as used to benchmark connectivity methods [8]) the recovered time-course correlation falls to 0.16 ± 0.07 , against 0.85 ± 0.05 for a per-trial eLORETA. The method is for evoked, multi-trial EEG and should not be applied to induced or connectivity data.

5.0.4. Other limits

The block count and rank are set by hand; the automatic component-selection of the BTTR framework [14] is the intended replacement. Deep sources degrade for all methods.

6. Discussion

Folding the lead field into the decomposition gives a model whose components are simultaneously spatial source maps, time courses and trial profiles, and are anatomical by construction. This is a different object from what a per-sample inverse returns, and from what decompose-then-localize tensor pipelines [12, 13] produce, where the spatial factors are abstract scalp patterns localized afterwards. For evoked, multi-trial data, where a small set of reproducible generators is the natural target, the joint localized decomposition is a useful addition to the toolbox: it identifies the dominant generators with their dynamics and trial behaviour in one step, with the focality and correlation-robustness reported above.

The results suggest a clear division of labour rather than a replacement. When the question is the precise location of one or a few point sources, a sparse-Bayesian solver or a beamformer is the better tool, and our benchmarks say so directly. When the question is which reproducible generators drive an evoked response, what their time courses are, and how they vary across trials, the component model answers it in a single estimate without a separate localization step and without assuming the generators are uncorrelated. The trial mode is the part that existing per-sample and decompose-then-localize pipelines have no direct analogue for: it exposes per-trial loadings that an amplitude map read across trials only approximates. Because the spatial factor is tied to the lead field, the components also remain interpretable as cortical maps rather than abstract scalp patterns that still have to be inverted.

Estimation is cheap and transparent. The greedy deflation fits one block at a time, each block an alternating least-squares loop in which the only nonlinear step is a row soft-threshold on the source factor; the dominant per-iteration cost is the lead-field products $\mathbf{L}^\top \mathbf{L}$ and $\mathbf{L}^\top \bar{\mathbf{M}}$, precomputed once. The temporal and trial factors act as an unsupervised consistency prior, so the ill-posed spatial update sees a denoised, structured target rather than a single noisy time frame, which is the mechanism behind the recovered-time-course fidelity in Table 1. The block rank L_r is the one tuning knob that matters for fidelity, and $L_r = 2$ already lifts the time-course correlation over the rank-one case at no focality cost; the block count can be set from

the variance-explained curve of the deflation, with the BTTR framework’s automatic selection [14] the intended drop-in.

We have kept the claims inside the evidence. The method is not the sharpest localizer, its focality margin over classical solvers is setup-dependent, and it is restricted to phase-locked data. Within that scope it does something the alternatives do not, and it does it on real evoked EEG. The natural next steps are a joint refit of all components to sharpen localization on dense grids, automatic selection of the component count and rank [14], and an extension of the trial factor beyond rank one to reach induced activity.

7. Conclusion

We presented a lead-field-constrained, row-sparse rank- $(L_r, L_r, 1)$ block-term decomposition that returns anatomically grounded spatiotemporal components of evoked multi-trial EEG: each component a focal source map, a recovered time course, and a trial loading, estimated jointly. The components recover the true generators on simulated data, the maps are focal, and the decomposition is robust to correlated sources where a beamformer fails. On real data the components localize contralaterally to the stimulated visual hemifield, consistent with the retinotopic expectation. We reported its limits with equal weight: it is not the sharpest point localizer, its focality margin is setup-dependent, and it is confined to phase-locked data. The complete pipeline is released open source.

CRedit authorship contribution statement

Axel Faes: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Maryam Amir Haeri:** Supervision, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics

Only openly available, de-identified datasets and simulated data were used; no new human data were collected.

Funding

This work was conducted within the project “Predicting the Development of Primary Liver Cancer Using the AI-HCC Model”, which is funded by ZonMw, The Netherlands Organisation for Health Research and Development.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used an AI-assisted coding and writing assistant (Claude, Anthropic) to help develop the analysis code and draft the manuscript. After using this tool the authors reviewed, verified, and edited the code and text, re-ran the released pipeline to confirm all reported results, and take full responsibility for the content of the publication.

Data availability

The full implementation (Python; NumPy/SciPy/scikit-learn/TensorLy/MNE-Python) is released with this paper, including all forward models, the realistic brain-noise simulation, the solver, the baselines (MNE/sLORETA/eLORETA/LCMV/Champagne), the metrics, and the scripts that regenerate every figure and table, together with the result CSVs that back every reported number. The repository is available at <https://github.com/TheAxeC/leadfield-btd-eeg>. The `fsaverage` and `sample` resources download through MNE-Python; the New York head model is publicly available [19].

References

- [1] C. M. Michel, D. Brunet, EEG source imaging: a practical review of the analysis steps, *Frontiers in Neurology* 10 (2019) 325.

- [2] R. Grech, T. Cassar, J. Muscat, K. P. Camilleri, S. G. Fabri, M. Zervakis, P. Xanthopoulos, V. Sakkalis, B. Vanrumste, Review on solving the inverse problem in EEG source analysis, *Journal of NeuroEngineering and Rehabilitation* 5 (1) (2008) 25.
- [3] M. S. Hämäläinen, R. J. Ilmoniemi, Interpreting magnetic fields of the brain: minimum norm estimates, *Medical & Biological Engineering & Computing* 32 (1) (1994) 35–42.
- [4] R. D. Pascual-Marqui, Standardized low-resolution brain electromagnetic tomography (sLORETA): technical details, *Methods and Findings in Experimental and Clinical Pharmacology* 24 (Suppl D) (2002) 5–12.
- [5] R. D. Pascual-Marqui, Discrete, 3D distributed, linear imaging methods of electric neuronal activity. Part 1: exact, zero error localization, *arXiv preprint arXiv:0710.3341* (2007).
- [6] B. D. Van Veen, W. Van Drongelen, M. Yuchtman, A. Suzuki, Localization of brain electrical activity via linearly constrained minimum variance spatial filtering, *IEEE Transactions on Biomedical Engineering* 44 (9) (1997) 867–880.
- [7] D. Wipf, S. Nagarajan, A unified Bayesian framework for MEG/EEG source imaging, *NeuroImage* 44 (3) (2009) 947–966.
- [8] E. González-Moreira, D. Paz-Linares, A. Areces-González, R. Wang, J. Bosch-Bayard, M. L. Bringas-Vega, P. A. Valdes-Sosa, Caulking the leakage effect in MEEG source connectivity analysis, *arXiv preprint arXiv:1810.00786* (2018).
- [9] L. De Lathauwer, Decompositions of a higher-order tensor in block terms—Part II: Definitions and uniqueness, *SIAM Journal on Matrix Analysis and Applications* 30 (3) (2008) 1033–1066.
- [10] A. Cichocki, D. Mandic, L. De Lathauwer, G. Zhou, Q. Zhao, C. Caiafa, H. A. Phan, Tensor decompositions for signal processing applications: From two-way to multiway component analysis, *IEEE Signal Processing Magazine* 32 (2) (2015) 145–163.
- [11] T. G. Kolda, B. W. Bader, Tensor decompositions and applications, *SIAM Review* 51 (3) (2009) 455–500.

- [12] F. Cong, Q.-H. Lin, L.-D. Kuang, X.-F. Gong, P. Astikainen, T. Ristaniemi, Tensor decomposition of EEG signals: a brief review, *Journal of Neuroscience Methods* 248 (2015) 59–69.
- [13] H. Becker, L. Albera, P. Comon, R. Gribonval, F. Wendling, I. Merlet, Brain-source imaging: From sparse to tensor models, *IEEE Signal Processing Magazine* 32 (6) (2015) 100–112.
- [14] A. Faes, F. Camarrone, M. M. Van Hulle, Single finger trajectory prediction from intracranial brain activity using block-term tensor regression with fast and automatic component extraction, *IEEE Transactions on Neural Networks and Learning Systems* (2022).
- [15] K. Sekihara, S. S. Nagarajan, *Adaptive Spatial Filters for Electromagnetic Brain Imaging*, Springer, 2008.
- [16] F. Cong, Q.-H. Lin, L.-D. Kuang, X.-F. Gong, P. Astikainen, T. Ristaniemi, Tensor decomposition of EEG signals: a brief review, *Journal of Neuroscience Methods* 248 (2015) 59–69.
- [17] S. Haufe, V. V. Nikulin, A. Ziehe, K.-R. Müller, G. Nolte, Combining sparsity and rotational invariance in EEG/MEG source reconstruction, *NeuroImage* 42 (2) (2008) 726–738.
- [18] B. Fischl, FreeSurfer, *NeuroImage* 62 (2) (2012) 774–781.
- [19] Y. Huang, L. C. Parra, S. Haufe, The New York Head—a precise standardized volume conductor model for EEG source localization and ESI, *NeuroImage* 140 (2016) 150–162.
- [20] L. Beltrachini, The analytical subtraction approach for solving the forward problem in EEG, *Journal of Neural Engineering* 16 (5) (2019) 056029.
- [21] P. A. Valdes-Sosa, et al., The Cuban Human Brain Mapping Project, a young and middle age population-based EEG, MRI, and cognition dataset, *Scientific Data* 8 (2021) 45.
- [22] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, D. Strohmeier, C. Brodbeck, R. Goj, M. Jas, T. Brooks, L. Parkkonen, M. Hämäläinen, MEG and EEG data analysis with MNE-Python, *Frontiers in Neuroscience* 7 (2013) 267.

- [23] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, D. Strohmeier, C. Brodbeck, L. Parkkonen, M. S. Hämäläinen, MNE software for processing MEG and EEG data, *NeuroImage* 86 (2014) 446–460.
- [24] A. Molins, S. M. Stufflebeam, E. N. Brown, M. S. Hämäläinen, Quantification of the benefit from integrating MEG and EEG data in minimum ℓ_2 -norm estimation, *NeuroImage* 42 (3) (2008) 1069–1077.
- [25] O. Hauk, M. Stenroos, M. S. Treder, Towards an objective evaluation of EEG/MEG source estimation methods—the linear approach, *NeuroImage* 255 (2022) 119177.