Blind Source Separation in Neuroscience

Anil Kamber[†,1], Hakan Ak[†,1], Alper T. Erdogan[2], Burak Acar[1],

[1]*Dept. of Electrical and Electronics Engineering, Bogazici University, Istanbul, Turkey*

[2]*KUIS AI Center, Koc University, Istanbul, Turkey*

Email: {[1]anil.kamber, [1]hakan.ak}@std.bogazici.edu.tr, [2]alperdogan@ku.edu.tr, [1]acarbu@bogazici.edu.tr

Introduction

- We assume that the brain operates in terms of subnetworks that cooperate to perform specific tasks. These subnetworks are presumed to be **sparse and overlapping**. For instance, multiple subnetworks might be active while the brain is performing a task.
- The aim is to identify these subnetworks by separating the source signals associated with distinct subnetworks.
- In this project, we brought **Polytopic Matrix Factorization (PMF)**, which provides "*identifiable polytopes*" to extend feature attributes of latent factors, to the neuroscience realm to extract latent vector components associated with distinct subnetworks [1].
- In the absence of ground truths for the sources expected to be separated from EEG signals, we used the best-fitted dipoles as ground truths, and residual variance as the error metric.

Methodology

$$\mathbf{X} = \mathbf{W}_g\mathbf{S}_g, \mathbf{W}_g \in \mathbb{R}^{M\times r}, \mathbf{S}_g \in \mathbb{R}^{r\times N}, \tag{1}$$

$$S_j \in \mathcal{P}, \quad j = 1,\ldots,N. \tag{2}$$

$$\mathcal{P} = \{\mathbf{x} \mid \langle \mathbf{a}_i, \mathbf{x}\rangle \le b_i,\ i = 1,\ldots,f\}. \tag{3}$$

$$\begin{aligned} &\underset{\mathbf{W}\in\mathbb{R}^{M\times r},\mathbf{S}\in\mathbb{R}^{r\times N}}{\text{maximize}} && \det(\mathbf{S}\mathbf{S}^T) \\ &\text{subject to} && \mathbf{X} = \mathbf{W}\mathbf{S}, \\ & && \mathbf{S}_{:,j} \in \mathcal{P}, \quad j = 1,\ldots,N. \end{aligned} \tag{4}$$

- $\mathcal{P}$ is chosen to be the ℓ_1 norm ball, since the relationship between the sparsity and ℓ_1 norm constraints is well-examined in [2], [3].

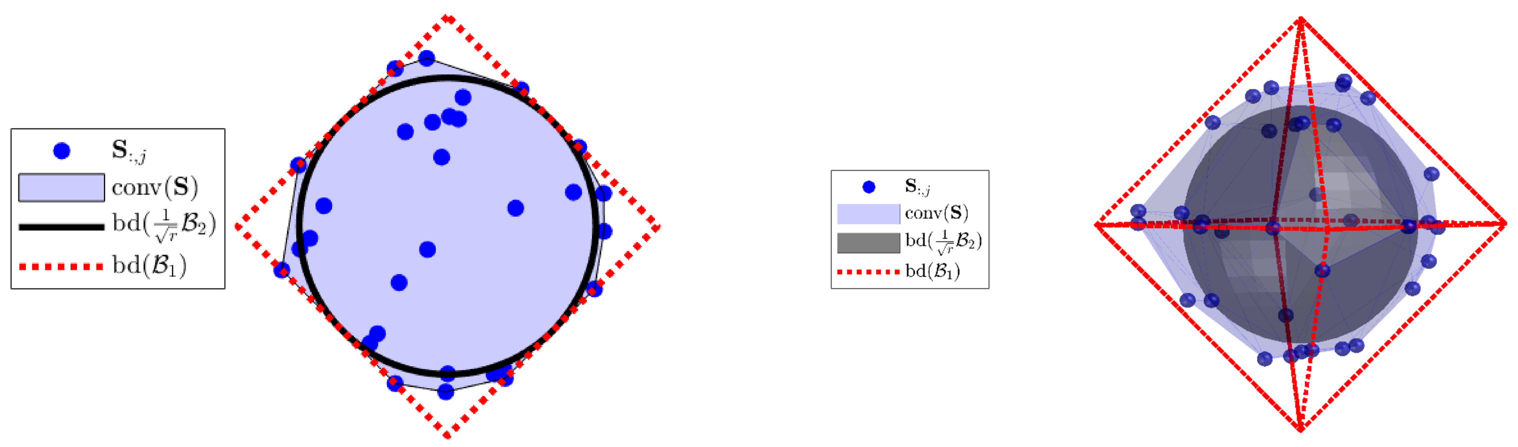

Figure 1: Comparison between sufficiently-scattered examples of 2-D and 3-D sparse PMF [1].

†These authors contributed equally to this work.

Results

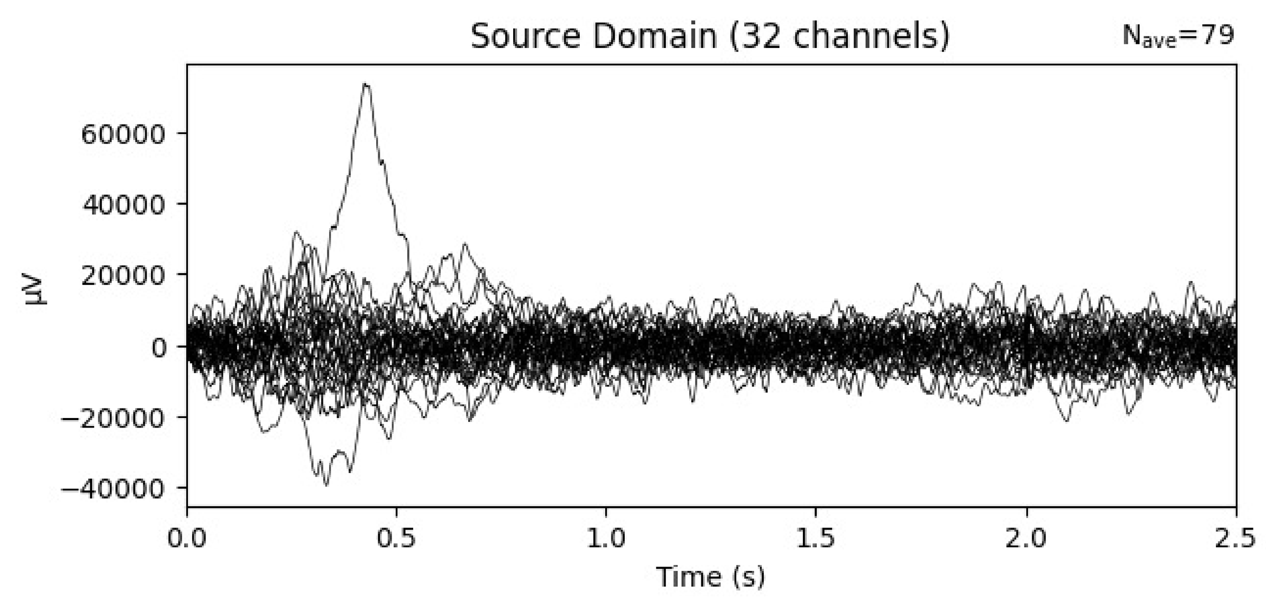

Figure 2: Average EEG activity in the source domain during selective visual attention event. (During this selective visual attention experiment, subjects were instructed to press a button with their right thumb when a colored square appeared in one of five horizontally arranged squares. They were to ignore circular disk stimuli [4]. On average, the subject presses the button 0.4 seconds after the square appears.)

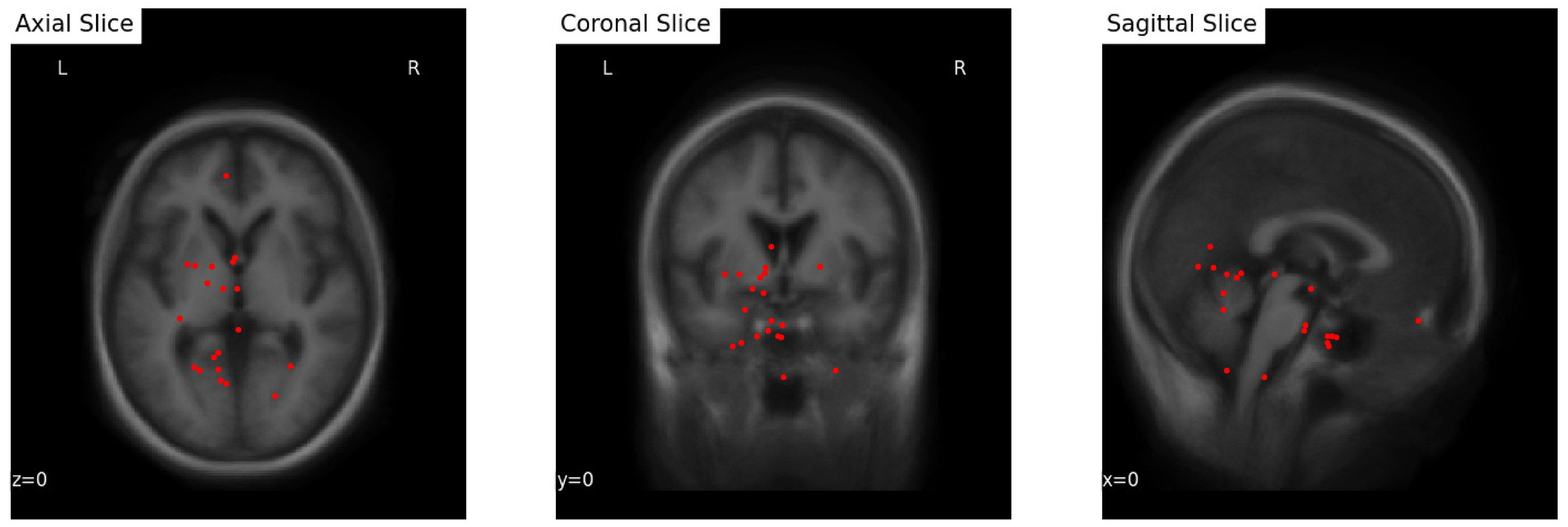

Figure 3: MNI coordinates of best fitted dipoles (sources) are projected onto middle slices of each view, for the selective visual attention experiment.

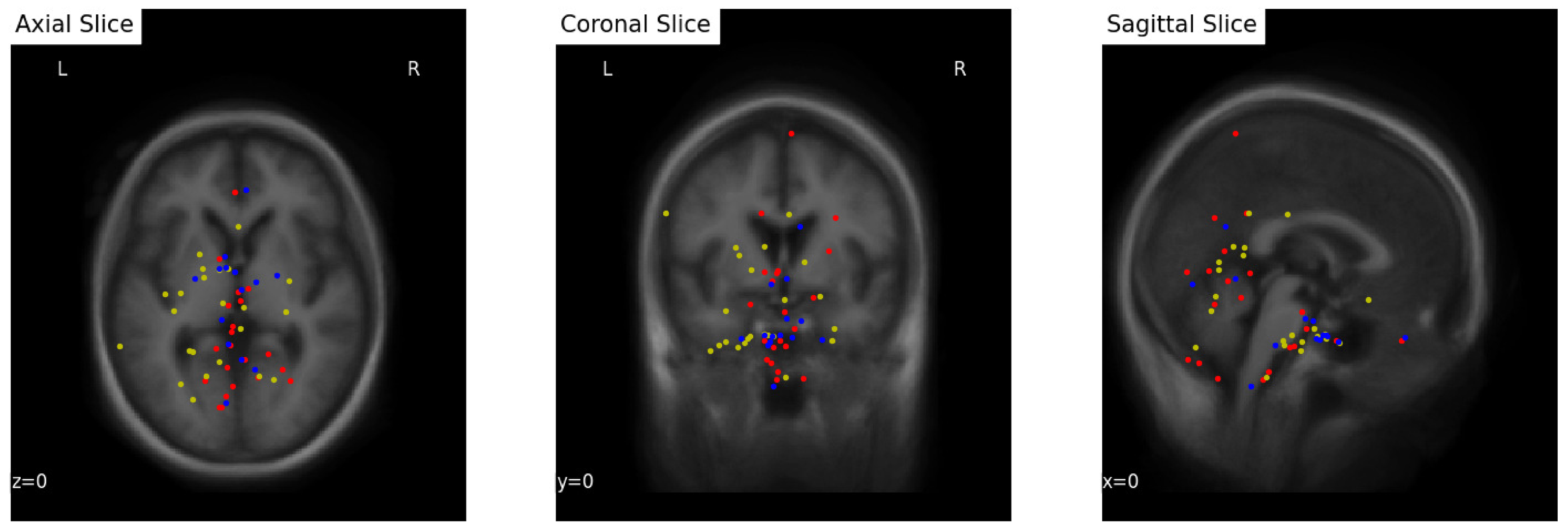

Figure 4: MNI coordinates of best fitted dipoles (sources) are projected onto middle slices of each view. For reproducibility concerns, the data has been divided into four sequences, each containing an equal number of visual events. Each sequence is regarded as an individual subject. Each color represents different subject.

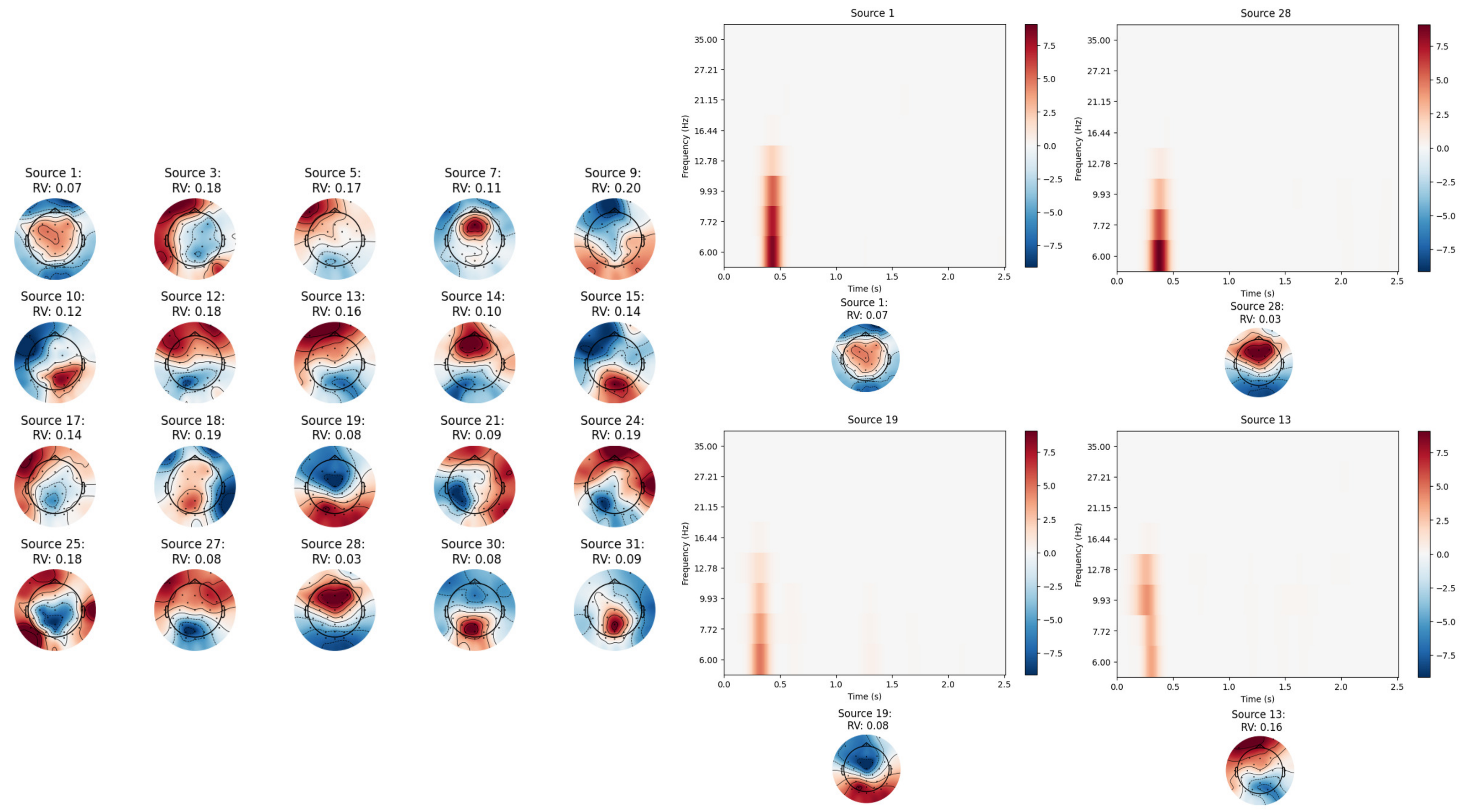

Figure 5: Brain topographic maps of separated sources with their residual variances. Due to the scaling ambiguity of PMF, the Morlet transform is utilized to identify event-related sources.

Future Work

- A processing pipeline utilizing PMF could be developed to differentiate between two groups by analyzing EEG sources during resting state or following a specific stimulus.
- Further research could investigate the feasibility of employing the PMF as a feature extractor and embedding it within a deep learning framework.

References

[1] G. Tatli and A. T. Erdogan, "Polytopic matrix factorization: Determinant maximization based criterion and identifiability," *IEEE Transactions on Signal Processing*, vol. 69, pp. 5431–5447, 2021.

[2] D. L. Donoho, "For most large underdetermined systems of equations, the minimal ℓ_1-norm near-solution approximates the sparsest near-solution," *Communications on Pure and Applied Mathematics*, vol. 59, no. 7, pp. 907–934, Jul. 2006.

[3] E. J. Candès and M. B. Wakin, "An introduction to compressive sampling," *IEEE Signal Processing Magazine*, vol. 25, no. 2, pp. 21–30, Mar. 2008.

[4] S. Makeig, M. Westerfield, T.-P. Jung, *et al.*, "Functionally independent components of the late positive event-related potential during visual spatial attention," *Journal of Neuroscience*, vol. 19, no. 7, pp. 2665–2680, 1999.