Causal Graphical Modelling of Functional Connectivity from Reconstructed EEG Sources

A. Faes[1,*], M. Fahimi Hnazaee[1], and M. Van Hulle[1]

[1]KU Leuven, Belgium
[*]Laboratorium voor Neuro- en Psychofysiologie, O&N2 Herestraat 49 - bus 1021, 3000 Leuven, Belgium.
E-mail: axel.faes@gmail.com

Introduction By placing EEG electrodes on the scalp, brain activity can be gauged, e.g. in response to an experimental paradigm. What is measured results from mixing activity from different sources within the brain. Of special interest are directional causal dependencies, or functional connectivity, between these different sources. We propose a new method based on graph theory and graph signal processing for modelling functional connectivity. [1]

Methods The Temporal Causal Discovery Framework, an attention-based convolutional neural network with a causal validation step, is used to discover causal relationships [2]. These causal relationships are used as a skeleton-solution in a Causal Graphical Process Model [3] [4].

Experiments A functional network was simulated in order to validate the developed method. The simulation assumes several steps: generation of brain sources with a given connectivity pattern, generation of noisy sources, forward modelling of brain and noisy sources using a given signal-to-noise ratio, generation of sensor noise, inverse modelling of resulting signal and connectivity estimation [5]. The connectivity pattern used was selected from [6], shown in equation 1.

$$\begin{cases} x_1(n) = 0.5x_1(n-1) - 0.7x_1(n-2) + 0.25x_2(n-1) + w_1(n) \\ x_2(n) = 0.7x_2(n-1) - 0.5x_2(n-2) + 0.2x_1(n-1) + 0.25x_3(n-1) + w_2(n) \\ x_3(n) = 0.8x_3(n-1) + w_3(n) \end{cases} \tag{1}$$

Results Within the simulation framework, 500 noisy sources were implemented with a signal-to-noise ratio of 0.9. Sensor noise was added with a signal-to-noise ratio of 0.9. As a forward model the 'New York Head Model' was used to map activity from brain sources to the scalp [7]. The resulting connectivity estimation is given in equation 2. These preliminary results show that the described method can accurately estimate simulated connectivity patterns.

$$\begin{cases} x_1(n) = 0.5x_1(n-1) - 0.4x_1(n-2) + 0.14x_2(n-1) + 0.14x_3(n-2) + 0.2x_2(n-1) \\ x_2(n) = 0.77x_2(n-1) - 0.28x_2(n-2) + 0.18x_1(n-1) + 0.31x_3(n-1) \\ x_3(n) = 0.8x_3(n-1) \end{cases} \tag{2}$$

References

[1] M. Gazzaniga and R. B. Ivry, *Cognitive Neuroscience: The Biology of the Mind: Fourth International Student Edition.* WW Norton, 2013.

[2] M. Nauta, D. Bucur, and C. Seifert, "Causal discovery with attention-based convolutional neural networks," *Machine Learning and Knowledge Extraction*, vol. 1, p. 312–340, Jan 2019.

[3] J. Mei and J. M. Moura, "Signal processing on graphs: Causal modeling ofunstructured data," *IEEE Transactions on Signal Processing*, vol. 65, no. 8, pp. 2077–2092, 2016.

[4] X. Dong, D. Thanou, M. Rabbat, and P. Frossard, "Learning graphs from data: A signal representation perspective," *IEEE Signal Processing Magazine*, vol. 36, no. 3, pp. 44–63, 2019.

[5] A. Anzolin, P. Presti, F. Van De Steen, L. Astolfi, S. Haufe, and D. Marinazzo, "Quantifying the effect of demixing approaches on directed connectivity estimated between reconstructed eeg sources," *Brain topography*, pp. 1–20.

[6] A. Omidvarnia, M. Mesbah, J. M. O'Toole, P. Colditz, and B. Boashash, "Analysis of the time-varying cortical neural connectivity in the newborn eeg: A time-frequency approach," in *International Workshop on Systems, Signal Processing and their Applications, WOSSPA*, pp. 179–182, May 2011.

[7] Y. Huang, L. C. Parra, and S. Haufe, "The new york head—a precise standardized volume conductor model for eeg source localization and tes targeting," *NeuroImage*, vol. 140, pp. 150–162, 2016.