nonparametricGGC_toolbox

If you use nonparametricGGC_toolbox for a paper or talk please include the following references:

1) M.F. Pagnotta, M. Dhamala, G. Plomp, Benchmarking nonparametric Granger causality: robustness against downsampling and influence of spectral decomposition parameters, NeuroImage. 183 (2018) 478–494. https://doi.org/10.1016/j.neuroimage.2018.07.046
2) M. Dhamala, G. Rangarajan, M. Ding, Analyzing information flow in brain networks with nonparametric Granger causality, NeuroImage. 41 (2008) 354–362. https://doi.org/10.1016/j.neuroimage.2008.02.020.

If you want to report bugs or provide suggestions please send an e-mail to:
mattia.f.pagnotta@gmail.com (subject: nonparametricGGC_toolbox).

Nonparametric GGC estimation

The three files *compute_nonparGGC_multitaper.m*, *compute_nonparGGC_wavelet_Morlet.m*, and *compute_nonparGGC_wavelet_Paul.m* are functions implemented in MATLAB® (The MathWorks, Inc.), which allow estimating Granger–Geweke causality (GGC) [1] from multivariate data using nonparametric methods based on spectral factorization [2,3]. More specifically, the first function enables GGC estimation based on multitaper method [4]; while, the other two functions allow a straightforward estimation of time-varying nonparametric GGC using Morlet and Paul wavelet transforms [5], respectively. The spectral factorization, which is needed in nonparametric methods, is based on Wilson's algorithm [6] and is performed through the function *wilson_sf.m*. Detailed comments about input/output of the functions and the different steps for GGC estimation are provided inside each script. For a more detailed description of nonparametric methods please refer to [2,3].

Simulation framework

The simulation framework comprises three MATLAB scripts:

- *sim_nonparGGC_CommonReference.m* relative to the common reference problem [7];
- *sim_nonparGGC_AdditiveNoise.m* relative to the problem of signal-to-noise ratio (SNR) imbalance between channels and the effects of additive noise [8];
- *sim_nonparGGC_StokesPurdon.m* relative to a recent claim of pitfall associated with the use of conditional GGC [9].

In each simulation, the function *compute_nonparGGC_multitaper.m* is used for estimating nonparametric GGC. Examples and detailed descriptions of the simulation framework are provided in the accompanied Data in Brief article.

References

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[3] M.F. Pagnotta, M. Dhamala, G. Plomp, Benchmarking nonparametric Granger causality: Robustness against downsampling and influence of spectral decomposition parameters, NeuroImage. 183 (2018) 478–494. doi:10.1016/j.neuroimage.2018.07.046.

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[9] P.A. Stokes, P.L. Purdon, A study of problems encountered in Granger causality analysis from a neuroscience perspective, Proc. Natl. Acad. Sci. 114 (2017) E7063–E7072. doi:10.1073/pnas.1704663114.