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**A nonparametric efficient evaluation of partial directed coherence.** (English) Zbl 1359.92016

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Summary: Studying the flow of information between different areas of the brain can be performed using the so-called partial directed coherence (PDC). This measure is usually evaluated by first identifying a multivariate autoregressive model and then using Fourier transforms of the impulse responses identified and applying appropriate normalizations. Here, we present another way to evaluate PDCs in multivariate time series. The method proposed is nonparametric and utilizes a strong spectral factorization of the inverse of the spectral density matrix of a multivariate process. To perform the factorization, we have recourse to an algorithm developed by Davis and his collaborators. We present simulations as well as an application on a real data set (local field potentials in a sleeping mouse) to illustrate the methodology. A detailed comparison with the common approach in terms of complexity is made. For long autoregressive models, the proposed approach is of interest.

**MSC:**

92C20 Neural biology
62P10 Applications of statistics to biology and medical sciences; meta analysis

**Keywords:**

partial directed coherence; connectivity; Granger causality; spectral factorization

**Software:**

MVGC; sapa

**Full Text:** DOI

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