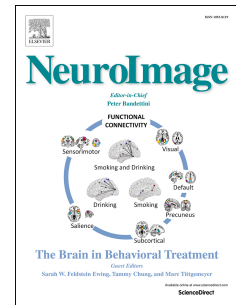


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Insight and Inference for DVARs

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Abstract

Estimates of functional connectivity using resting state functional Magnetic Resonance Imaging (rs-fMRI) are acutely sensitive to artifacts and large scale nuisance variation. As a result much effort is dedicated to preprocessing rs-fMRI data and using diagnostic measures to identify bad scans. One such diagnostic measure is DVARs, the spatial **root mean square** of the data after temporal differencing. A limitation of DVARs however is the lack of concrete interpretation of the absolute values of DVARs, and finding a threshold to distinguish bad scans from good. In this work we describe a sum of squares decomposition of the entire 4D dataset that shows DVARs to be just one of three sources of variation we refer to as *D*-var (closely linked to DVARs), *S*-var and *E*-var. *D*-var and *S*-var partition the sum of squares at adjacent time points, while *E*-var accounts for edge effects; each can be used to make spatial and temporal summary diagnostic measures. Extending the partitioning to global (and non-global) signal leads to a rs-fMRI DSE table, which decomposes the total and global variability into fast (*D*-var), slow (*S*-var) and edge (*E*-var) components. We find expected values for each component under nominal models, showing how *D*-var (and thus DVARs) scales with overall variability and is diminished by temporal autocorrelation. Finally we propose a null sampling distribution for DVARs-squared and robust methods to estimate this null model, allowing computation of DVARs p-values. We propose that these diagnostic time series, images, p-values and DSE table will provide a succinct summary of the quality of a rs-fMRI dataset that will support comparisons of datasets over preprocessing steps and between subjects.

Keywords: DVARs, Mean Square of Successive Differences, Autocorrelation, sum of squares Decomposition, time series, fMRI, Resting-State

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