Local Dimension-Reduced Dynamical Spatio-Temporal Models for Resting State Network Estimation

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Abstract. Resting-state Functional Magnetic Resonance Imaging (FMRI) analysis has consistently shown the presence of specific spatial activation patterns. Independent component analysis (ICA) has been the analysis algorithm of choice even though its underlying assumptions preclude deeper connectivity analysis. By combining novel concepts of group sparsity with contiguity-constrained clusterization, we developed a new class of Local dimension-reduced Dynamical Spatio-Temporal Models (LDSTM) for estimating whole-brain dynamical models whereby the causal relationships between well localized spatial components can be identified. Experimental results of LDSTM on group resting-state FMRI data reveal physiologically plausible spatio-temporal brain connectivity patterns among participants.

Keywords: Resting-State FMRI, Spatio-Temporal Models, Brain Connectivity, Multiscale Analysis and Sparsity.

1 Introduction

In resting-state FMRI data analysis there is an ever growing and pressing need for accurately describing how brain regions are dynamically interrelated [3]. Due to the neuro-physiological nature of the BOLD signal, resting-state interactions are inseparable (in space and time) so that splitting the problem into separate space and time approaches is unrealistic specially if the focus lies in characterizing large spatial scale changes due to subtle interactions originating from a small number of regions of interest. The chief challenge is that any Dynamical Spatio-Temporal Model (DSTM) of FMRI data sets demands many parameters to describe what also is a large number of observed variables that nonetheless enjoy a great deal of spatial redundancy. In addition, most DSTMs in current use are problematic when it comes to estimating the spatial origin of signal variability as often only a relatively small sample size is available under largely unfavourable SNR (Signal-to-Noise) conditions [6,16,20,23].

Here we examine new classes of dimension-reduced DSTMs for resting-state network estimation. Dimension-reduced DSTMs were introduced by Wikle and Cressie...
to capture nonstationary spatial dependence under an optimal state representation via the Kalman filter thereby turning them into effective tools for modelling spatially continuous phenomena that change rapidly in space. In the original Wikle-Cressie formulation, the DSTM invokes an \textit{a priori} defined orthogonal basis to expand the redistribution kernel of a discrete time/continuous space linear integro-difference equation (IDE) in terms of a finite linear combination of spatial components. This idea was further supported in and extended in who considered parameterized redistribution kernels of arbitrary shape that meet homogeneity conditions in space and time. Even though the change of basis proposed in improve one’s understanding of high-dimensional processes, it by no means ensures sparse solutions which are key to achieving statistically robust dynamical descriptions.

Robustness is frequently sought by indirect means as in LASSO regression, in basis pursuit for model selection and denoising, in sparse component analysis for blind source separation and in iterative thresholding algorithms for image deconvolution and reconstruction. These methods promote sparsity by maximizing a penalized loss function via a compromise between the goodness of fit and the number of basis elements that make up the signal. Recently, more attention has been given to group sparsity, where groups of variables are selected/shrunken simultaneously rather than individually (for a review see) by minimizing an objective function that includes a quadratic error term added to a regularization term that considers \textit{a priori} beliefs or data-driven analysis to induce group sparsity.

This paper presents a state-space formulation suited to data sets of high dimensionality, such as FMRI, by taking advantage of spatial wavelet analysis to provide a data representation requiring fewer significant parameters. We combine group sparsity and contiguity-constrained clusterization to initialize an Expectation Maximization (EM) algorithm constructed especially to identify Local dimension-reduced DSTM (LDSTMs) whose columns of the observation matrix act as point-spreading functions. We used simulated data to evaluate our approach’s ability for signal recovering and model estimation detection compared to the traditional EM algorithm. Our new method was also used to study resting-state patterns of brain activation in real group FMRI data from healthy volunteers under a Multiplexed Echo Planar Imaging sequence (allowing very short repetition time).

2 Problem Formulation

DSTM problems may be formulated as state space models where space-related measurements \( z_t \) depend on the dynamical evolution of a suitably defined state \( x_t \) through a linear gaussian model

\[
\begin{align*}
  x_t &= H x_{t-1} + w_t, \\
  z_t &= A x_t + v_t,
\end{align*}
\]

where \( z_t \) is an \( M \) dimensional column vector of observed signals at time \( t \), \( x_t \) is an \( K \) dimensional column vector of unknown states, \( A \) is an unknown \( M \times K \) observation matrix, \( H \) is an unknown \( K \times K \) state-transition matrix, \( w_t \) is an innovation process and