Data augmentation in Rician noise model and Bayesian Diffusion Tensor Imaging

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By measuring in vivo the microscopic diffusion of water molecules, diffusion Magnetic Resonance Imaging (dMRI) is the only noninvasive technique which can detect diffusion anisotropies, which correspond to nervous fibers in the living brain. Spectral data from the displacement distribution of water molecules is collected by a magnetic resonance scanner. From the statistical point of view, inverting the Fourier transform from sparse and noisy spectral measurements is a non-linear regression problem. Diffusion tensor imaging (DTI) is the simplest modeling approach postulating a Gaussian displacement distribution at each volume element (voxel). Usually diffusion tensor estimation is based on a linearized log-normal regression model that fits dMRI data at low frequency (b-value). This approximation fails to fit the high b-value measurements which contain information about the details of the displacement distribution but have a low signal to noise ratio (SNR). We deal with the Rician noise model for the full range of b-values. Using data augmentation to represent the likelihood, the non-linear regression problem is reduced to the framework of generalized linear models. We construct a Bayesian hierarchical model, in order to perform simultaneously estimation and regularization of the tensor field. The Bayesian paradigm is implemented by Markov chain Monte Carlo with Gibbs-Metropolis updates, and alternatively, with the Variational Bayes approach.

Keywords: Generalized Linear Model, Gaussian Markov random field, Markov chain Monte Carlo, Poissonization, Rician noise, Variational Bayes.

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