BRANDI: Bayesian Regularisation of Advanced Neurological Diffusion Imaging

Susan Doshi[1], Derek Jones[2], and Daniel Barazany[2,3]

[1]*Computer Science and Informatics, Cardiff University, Cardiff, Glamorgan, United Kingdom,* [2]*CUBRIC, Cardiff University, Cardiff, United Kingdom,* [3]*Department of Neurobiology, Tel Aviv University, Tel Aviv, Israel*

Purpose

Advanced diffusion imaging methods specify a model which explains the MR signal loss using a set of parameters (e.g. axon orientation and diameter). These are generally estimated on a voxel-by-voxel basis, without taking into account the spatial correlations we know to be present. But from an anatomical perspective, we expect microstructure to vary smoothly within coherent white matter structures – this knowledge is not currently exploited.

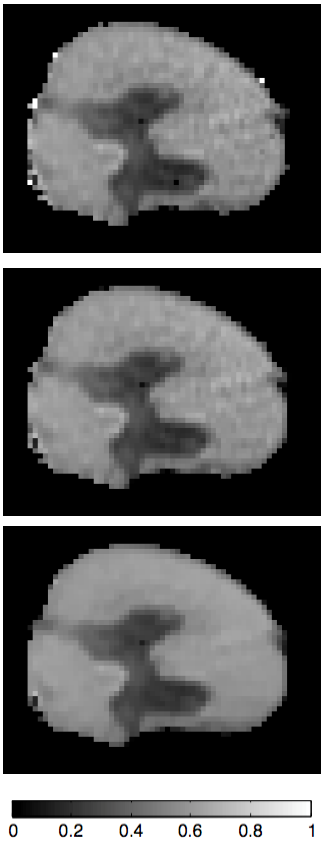
We describe here a novel application of Bayesian statistical modelling, which allows us to exploit spatial correlations in the underlying physical parameters in order to obtain better estimates of these parameters. By incorporating knowledge of smoothness at the estimation stage, we exploit more information than if we smooth as a post-processing step.

Methods

We demonstrate our approach using images of an *ex-vivo* porcine spinal cord as a biological phantom. This was scanned on a 7T/30 Bruker Biospec equipped with 400mT/m gradient unit. We acquired data to fit the CHARMED model[1] using a stimulated echo EPI pulse sequence with the following parameters: Δ/δ=20/3.2ms; b-values of 170,300,460,670,1000s/mm^2 with 16 non-collinear directions for each shell, with two B_0 measurements.

The CHARMED model describes the signal loss due to diffusion in terms of hindered and restricted components, identified with extra- and intra-axonal water respectively. In our Bayesian paradigm, we use this model for the likelihood of the data given the parameters. To this, we add a new prior probability distribution for the parameters. We use a Markov random field (MRF) model, where we define the prior probability of the parameters in a voxel, given its neighbours.

This framework is extremely flexible. We can encode many different types of information in the prior, including spatial smoothness. Parameter values with a large 'distance' from their neighbours are penalised. We define the distance between the tensors describing the restricted component using a geodesic distance defined on a Riemannian manifold of tensors[2]. The distance between the angular components is $(1-|u\cdot v|)$, where u and v are the vectors describing the directions of the restricted components. For the other parameters, we use the absolute difference in the value.



The penalty does not have to be isotropic – we can allow parameters to differ across edges, but smooth more homogeneous areas. Structure in one part of the data can guide the fitting in another: for example, we could smooth the estimates of radial diffusivity, but not across edges which emerge in the estimates of axon orientation. We use Markov chain Monte Carlo (MCMC) to sample from the posterior distribution of the parameters.

Results

The images show the estimates of the restricted fraction, with differing levels of correlation in the prior. From top to bottom: no correlation (conventional voxel-wise reconstruction), low correlation (some smoothing), high correlation (more smoothing). Even with a high level of smoothing in the homogeneous areas, the choice of prior has preserved the edges very well.

Discussion

A Bayesian model has been used to regularise estimates of myelin water fraction[3]. An isotropic prior encoded prior expectations of smoothness, with estimation carried out block-wise. Previous work on simultaneous estimation of microstructure and the connectome[4] estimated the microstructural parameters (assumed constant) along tracts (from a pool created by tractography).

Expressing the parameters as a realisation of an MRF and using MCMC provides a more flexible framework. We have illustrated this using the CHARMED model, but the Bayesian framework could be used to improve the estimates of other parameters. Working on a local scale with an MRF model allows us to make fewer assumptions about the expected variation in microstructure, with the ability to jointly estimate directional and microstructural information on a local scale.

Conclusion

We have illustrated the benefits of applying Bayesian statistical methods to advanced diffusion imaging, using prior information (based on anatomical knowledge) to regularise parameter estimates. To the best of our knowledge, this is the first time a Bayesian framework with an MRF model has been used with these data.

References

1. Assaf Y, Freidlin RZ, Rohde GK, Basser PJ. New modeling and experimental framework to characterize hindered and restricted water diffusion in brain white matter. Magn Reson Med. 2004 52(5):965-78.

2. Pennec X, Fillard P, Ayachea N. Riemannian Framework for Tensor Computing. International Journal of Computer Vision. 2006 66(1):41–66.

3. Kumar D, Thanh DN, Gauthier SA, Raj A. Bayesian Algorithm Using Spatial Priors for Multiexponential T2 Relaxometry From Multiecho Spin Echo MRI. Magn Reson Med. 2012 68(5):1536-43.

4. Sherbondy AJ, Rowe MC, Alexander DC. MicroTrack: an algorithm for concurrent projectome and microstructure estimation. Med Image Comput Comput Assist Interv. 2010;13(Pt 1):183-90.