Spatial random effects modelling of crossing fibre voxels in diffusion MRI

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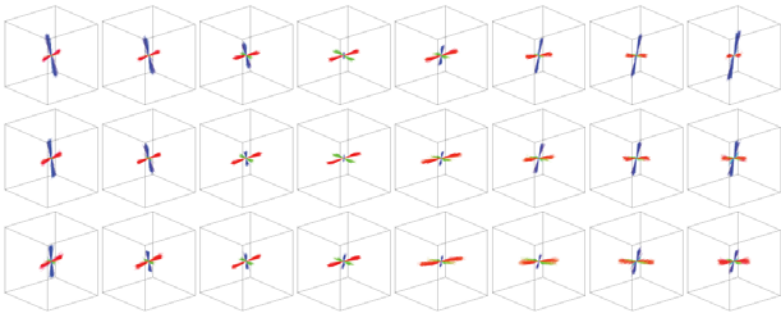
Introduction Diffusion tractography has rapidly become a prominent MRI technique, one that is used as a neurosciences research tool and offers promise as an aid to clinical decision making in neurosurgery. Routine clinical use will, however, depend on a refinement of existing algorithms in order to improve performance in terms of false positives and false negatives (failure to locate established pathways).

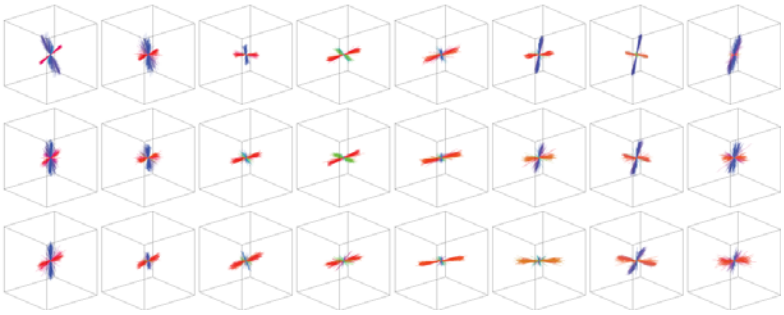
A common feature of the tractography algorithms used to date is the independent voxel-by-voxel approach that is adopted. Random effect (RE) models are a category of regression model in which one, or more, of the regression coefficients captures the fundamentally random behaviour of a cluster of units under consideration (voxels in the present analysis). They provide a formal approach to combining the information provided by a cluster of units and, in general, provide better estimates than those typically obtained by multiple single unit analyses. This abstract provides evidence to show that spatial random effects modelling (based on a Markov random field treatment) provides improved probabilistic information on crossing fibre voxels. The analyses were performed using Markov chain Monte Carlo (MCMC) simulation, as described elsewhere[1].

Methods Diffusion-weighted images were acquired using a b-value of 1000 s mm^{-2} and 20 directions, with two averages. Spatial random effect analyses were performed using a full measurement model that incorporates the 'mixture model' outlined by Behrens et al.[2] The main feature of the model is the rotation matrix which relates white matter orientation to the coordinate system defined by the magnetic field gradients. The spherical coordinates and b_0 signal intensity were assigned spatial (intrinsic Gaussian conditional autoregressive) priors, while the remaining parameters were assigned uninformative exchangeable prior distributions, except for the imposition of various physical constraints. Gibbs sampling was performed using WinBUGS (http://www.mrc-bsu.cam.ac.uk/bugs), together with the spatial prior provided by the car.normal function in the GeoBUGS addon to WinBUGS. Programs were written using the WinBUGS development interface[3]. Various convergence tests were performed using an R implementation of CODA (http://www.mrc-bsu.cam.ac.uk/bugs).

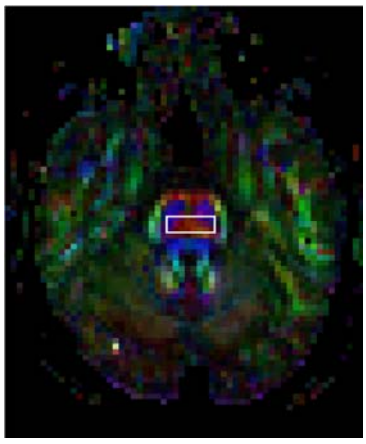
Spatial prior



Independent voxels treatment



Results The figure compares the results obtained with the spatial random effects model and those generated under the independent voxels treatment using data taken from the pons of a single subject. The location of the selected 3 by 8 region-of-interest is shown in the accompanying FA map. The results are displayed in the form of an array of vector cluster plots obtained by resampling the MCMC output, using 100 samples taken from the spherical coordinate posterior distribution for each component scaled by their respective volume fractions. In general, the spatial model yields tighter, better resolved components than the independent voxels analysis. In some voxels the spatial treatment appears to reveal additional structure.



Discussion and Conclusion This work is a continuation of a previous investigation into an MCMC RE modelling of crossing fibre MR diffusion data[4]. Previously we compared a number of models, including a spatial and exchangeable RE model. Here we focus on the spatial treatment. The results indicate that the intrinsic Gaussian conditional autoregressive prior performs particularly well, especially when applied to small collections of voxels, as shown here for a 3 by 8 region-of-interest. Our experience to date indicates that modelling larger regions, e.g., 10 by 10, leads to poorer resolution. This is not entirely unexpected because the spatial prior, despite being adaptive (the precision parameter is assigned a distribution), is spatially invariant. Consequently, the spatial prior must be compromised when dealing with a large area that is heterogeneous in structure. The results presented here indicate that the spatial RE model can be applied to a region in which neighbouring voxels differ markedly in structure, and that the underlying spatial heterogeneity in orientation is maintained.

References [1] King, MD. et al. doi:10.1016/j.neuroimage.2008.09.058 [2] Behrens, TEJ. et al. NeuroImage 34 :144-155 (2007). [3] Lunn, D. The ISBA Bulletin 10:10-11 (2003). [4] King, MD. et al. Proc. Intl. Soc. Mag. Reson. Med. 16:1857 (2008).