Using fractional anisotropy neighbourhood information in a Bayesian based regularisation technique for DTI

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Introduction

The information provided by Diffusion tensor MRI (DT-MRI) can be very useful in characterising the anisotropy of the brain [1,2]. However, the estimates of anisotropy produced by the single tensor model [3], such as the widely used fractional anisotropy (FA), can be highly dependent on noise. In fact, if the noise is known to be on a level witch can significantly affect the outcome of the model fit, then the uncertainty in the model parameters needs to be characterised if any useful information is to be extracted from the data. For this reason, Markov Chain Monte Carlo (MCMC) techniques [4] have been successfully used to estimate a probability distribution function (PDF) for the DT-MRI model parameters. The standard deviation (s.d.) of this PDF is a good marker for confidence in the results.

Regularisation techniques, which aim to reduce the effect of noise on the calculated parameters, can be applied and there are some examples in the literature (e.g. [5-7]). In this abstract we present a regularisation technique based on the information provided by the neighbouring voxels, by taking advantage of the prior term in the MCMC algorithm.

Theory and Methods

Bayesian techniques allow prior knowledge of model parameters to be incorporated in the calculation of their PDFs. Bayes relation is given by (1). The term $P(\omega|M)$ is the probability of the vector of model parameters (ω) given the model (M), and is called the prior probability. In our case, $\omega=(\lambda_1, \lambda_2, \lambda_3, \theta, \phi, S_0)$, where λ_1, λ_2, and λ_3 represent the eigenvalues of the diffusion tensor, θ and ϕ characterise the diffusion direction, and S_0 is the baseline signal. The aim of the regularisation technique described in this abstract is to construct a prior based on the FA of the neighbouring voxels to supply information to the Markov chain about how anisotropic we expect a certain voxel to be. The idea behind this prior is that the variation of FA along a fibre tract should be smooth, and therefore if there is a tract connecting two neighbour voxels, the FA variation between these two voxels should be small. In addition, the values of this prior should be high if it is very likely that the voxel of interest and its neighbour are connected and small if there is very poor evidence for this connection. A previous run of the Markov chain is used to generate N samples of the model parameters' PDFs for each voxel's neighbour. The full prior will be given by (2). K=6 is the number of first neighbours, $V(\theta_i^n, \phi_i^n)$ is the volume of fibres which can enter the voxel of interest form the neighbour i (assuming the fibres are aligned and there is no fibre curvature), Δ_{Si}^n (3) accounts for the difference between the measured signal and the estimated signal for neighbour i obtained with the n^{th} vector of sampled parameters (D_i^n represents the diffusion tensor, and N_{vol} the number of volumes in the diffusion MRI dataset), and $g(FA_i^n, \sigma)$ (4) accounts for the difference between the n^{th} estimate of FA for neighbour i, and FA in the voxel of interest. ε is a number smaller then the other terms, which ensures that the prior is never zero. This prevents the Markov chain from getting stuck when this prior is a poor description of the neighbouring anatomy.

The neighbourhood prior algorithm was applied to datasets of healthy volunteers (voxel dimensions 2.0 x 2.0 x 2.0 mm^3) acquired with a Siemens 3T Tim Trio.

$$P(\omega / data) = \frac{P(data\,|\,\omega, M)\,P(\omega\,|\,M)}{P(data\,|\,M)} \quad (1)$$

$$P(\lambda_1, \lambda_2, \lambda_3\,|\,M) = \varepsilon + \sum_{i=1}^{K}\sum_{n=1}^{N} g(FA_i^n, \sigma)\,V(\theta_i^n, \phi_i^n) / \Delta_S^n \quad (2)$$

$$\Delta_{Si}^n = \sqrt{\sum_{v=1}^{N_{vol}} \left(S_{iv}^n - S_{0i}^n e^{-b\vec{r}_v^{\,T} D_i^n \vec{r}_v}\right)^2} \quad (3)$$

$$g(FA_i^n, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(FA_i^n - FA)^2}{2\sigma^2}} \quad (4)$$

Results and Discussion

Fig. 1 shows the results obtained for the s.d. of the PDFs obtained for FA when no neighbour prior is applied, plotted against the results obtained for the s.d. of FA when we use the neighbourhood prior. Each point in this plot represents a voxel in the dataset. The straight line corresponds to y=x, and therefore this figure shows that the neighbourhood prior reduces the standard deviation of the estimated PDF. As mentioned previously, this standard deviation is a good marker for confidence in the results, and therefore this result shows that the use of the prior contributes to the minimisation of the uncertainty of the results due to noise. The points that distinctly lie above the line y=x correspond to noise voxels outside the brain, where the neighbourhood prior is expected to have very little effect as noise voxels are not connected to each other.

Another important effect of this prior is shown in Fig.s 2 and 3. Fig. 2 shows the mean value (m.v.) of the PDF obtained for FA for 5 different voxels in the brain. For each of these voxels, 50 samples of the FA PDF were collected, and their mean values calculated. This procedure was repeated 20 times, with and without the neighbourhood priors. The mean values obtained for different trials when the neighbourhood priors are applied are much more stable than the ones obtained without this prior, which shows that this method increases the repeatability of the FA estimates. Fig. 3 shows three FA maps obtained for three runs of the model fit when the priors are applied (top row) and when we use only flat priors (bottom row). The maps obtained with the neighbourhood prior show very little change in contrast, while the ones obtained without this prior show significant variability (see for example the region inside the blue rectangle).

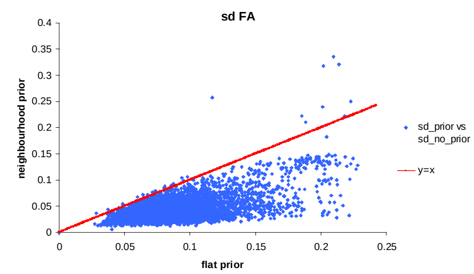

Fig. 1 – Effect of the neighbourhood prior in the standard deviation of the FA PDFs for each voxel of one dataset.

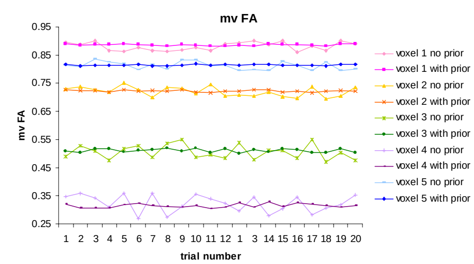

Fig. 2 – Effect of the neighbourhood prior in the mean value of the FA PDFs 5 voxels of one dataset.

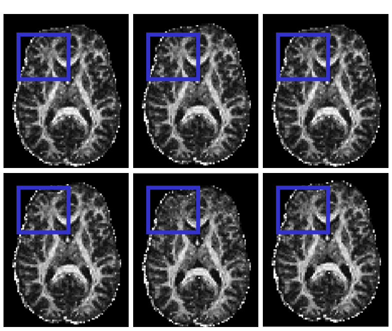

Fig. 3 – FA maps obtained with and without the neighbourhood prior.

Conclusion

A new regularisation method for DT-MRI has been introduced, which is capable of improving the confidence in the FA maps obtained from diffusion weighted MRI datasets. The regularisation is applied to the priors rather than the data itself, meaning that the fit is biased towards spatially consistent solutions but only when supported by the data. The prior also allows violations of the expected behaviour if it did not describe the data well, by ensuring the regularisation prior never returns zero, which would result in a static Markov chain, which would falsely appear to give very good confidence in the sampled parameters.

References

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