Determination of local fibre configuration using Bayesian neighbourhood tract modeling

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Introduction

Current state of the art methods for tractography typically operate by propagating a track based on the local fibre orientation information at any given point, independently of any other generated tracks. Such methods do not make use of additional information that might be available from fitting all tracts concurrently, which would allow the probability of one tract to be affected by the presence of another. Recent studies have used this type of information to improve the estimate of the local fibre configuration. King et al. [1] used a Bayesian random effects modelling approach to improve fibre orientation estimates in areas of complex tract crossings, based on the estimates of adjoining voxels. In contrast, Savadjiev et al. [2] used helical curve approximations to decide between, single fibre, crossing, fanning or bending models in each imaging voxel. In this study we introduce a richer local fibre configuration model, which represents multiple tract segments explicitly by 3D curves with associated volumes. The resulting local neighbourhood representations incorporate not only fibre orientation estimates but also estimates of the tract segment curvature and sub-voxel positioning.

Methods

We define our problem in terms of the Bayesian framework and seek to represent the posterior distribution of the complete neighbourhood tract configuration via samples generated from a Markov-chain Monte-Carlo (MCMC) method. In our representation, each tract is modelled by a 3D curve 'backbone' and a grid of perturbations about this backbone over two axes. The perturbation axes define the volume the tract, and also allow the tract width to widen, flatten and fan. The tract backbones and perturbations are parameterised by second order 3D Fourier Descriptors (FD) [3] and a prior distribution is imposed on their curvature and the magnitude of the perturbations. The endpoints of the backbones are constrained to lie on the smallest sphere that encloses the local neighbourhood (3x3x3 in this study) to ensure that the tract segments do not terminate within the modelled white matter structure. Each neighbourhood is populated with more tracts than are required, with the excess tracts allowed to move close to the sphere surface where they will have little or no contribution to the estimated signal.

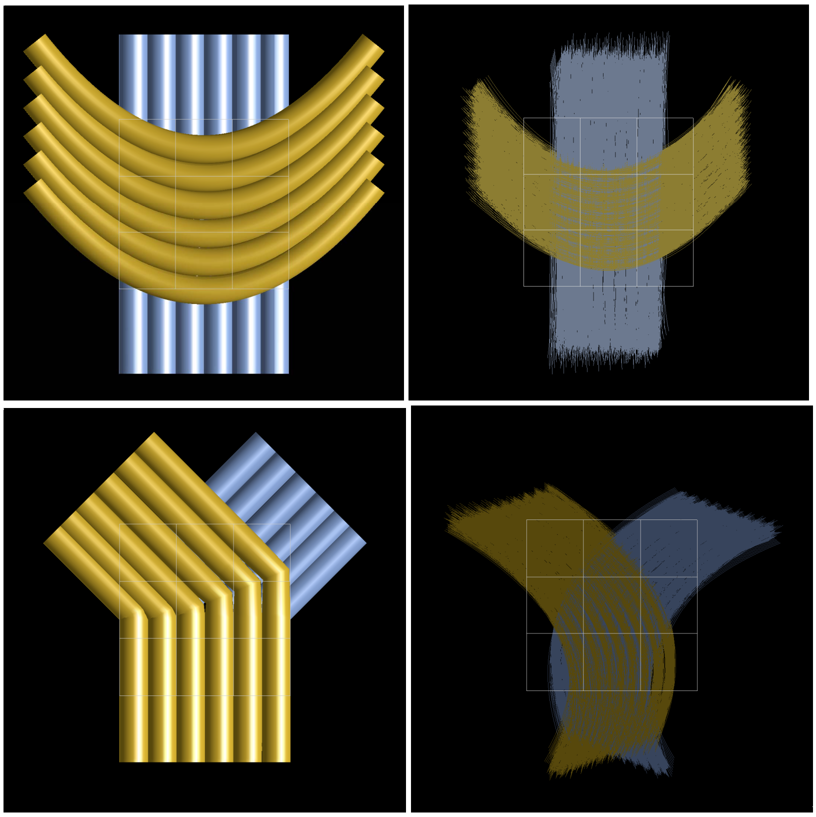

Figure 1: *Left*: Test structures consisting of six layered alternating fibre paths. *Right*: Samples from the posterior distribution of tract-segment parameters, given the DW-MR images simulated from the test structures. Each modelled tract segment in the posterior samples is displayed by interpolating 9x9 perturbations. Images were simulated with SNR 15 in 60 directions. *Top:* Crossing between straight and curving fibre paths. *Bottom:* Branching Y-fibre structure. In all cases the grid indicates the 3x3x3 voxel neighbourhood.

The expected DW intensities are generated from sample points taken at fixed intervals along each backbone and their associated perturbations. The orientation of the path at these points is convolved with an axially symmetric response function [4], to give the corresponding signals in each of the DW orientations. The signals are then trilinearly interpolated to the centres of the surrounding voxels. The noise distribution about each of the expected voxel intensities is assumed to be Gaussian. The (un-normalised) posterior probability of the tract configuration, given the image data, is then computed via Bayes' rule.

Samples are drawn from the posterior distribution using the Metropolis-Hastings MCMC algorithm. The tracts were initialised as straight paths from randomly chosen points on the sphere surface [5]. 100 samples were taken from the posterior, sampling every 10,000 iterations after a burn-in period of 100,000 iterations.

The algorithm was tested on simulated tract configurations (Figure 1) created using 36 fibre paths, organised in alternating layers half a voxel thick. The signal response function is calculated assuming a diffusion tensor model (FA = 0.8 and ADC 5×10^{-4}mm^2/s), simulated at b=3000s/mm^2. The DW datasets were simulated in 60 uniformly distributed directions, with Gaussian noise corresponding to an SNR of 15.

Results

As shown in Figure 1, the samples from the posterior show good correspondence with the test structures. The algorithm is able to distinguish between tract curvature, crossing, and branching. The algorithm also recovers the correct relative position of the layers, i.e. yellow above blue (Figure 1, right).

Discussion

A new algorithm that uses a rich local neighbourhood model of tract segments was introduced, which models the uncertainty of the data in a Bayesian framework. Each sample of the posterior distribution contains an estimate of the complete local neighbourhood configuration. Since all tract segments are taken into consideration simultaneously, each tract segment will only be probable if it is consistent with all other segments in the local neighbourhood. Once the local configuration is obtained, the information provided is relevant for the centre voxel of the modelled local neighbourhood; for applications such as fibre-tracking, this analysis would then be repeated for every voxel and the tracking performed over this improved representation of the tract configurations. While King et al. [1] and Savadjiev et al [2] use the local neighbourhood to inform the fibre configurations estimates in each voxel, the tract representations they use discard neighbourhood information concerning volume and sub-voxel positioning that could be used to better inform tracking algorithms. The novel tract segment model presented in this study is flexible enough to represent a wide range of tract configurations, while still retaining a low number of parameters, 25 per tract segment. It is anticipated that the resulting local estimates will help resolve regions of complex crossing fibres, better characterise curving tracts, and reduce noise accumulation present in streamlines. This information is expected to lead to improved tracking-tracking algorithms.

References

1. King, MD et al. 2009. *NeuroImage*, 44, 753. **2**. Savadjiev, P et al. 2008. *NeuroImage*, 41, 58. **3**. Chung, MK et al. 2008. Tech. Report 204, University of Wisconsin, Madison, USA. **4**. Tournier, J-D et al. 2004. *NeuroImage*, 23, 1176. **5**. Close, T et al. 2009 *NeuroImage*, 47, 1288.