

Regularized diffusion tensor MRI for high angular resolution ODF estimation and fibre tractography

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Introduction High angular resolution diffusion (HARD) MRI can be used to infer multiple subvoxel fibre directions [1-2], and this information can be used to improve the precision of fibre tractography over that achieved with the single diffusion tensor model [3]. Acquisition schemes suitable for HARD reconstruction typically require 100-500 diffusion encoding directions and $b \geq 3000$ s/mm². We have developed a regularization method [4] for inferring high angular resolution orientation distribution functions (ODFs) directly from the diffusion ODF field calculated using a single-tensor model, by considering information from neighbouring voxels. This is a powerful technique in that it allows us to infer multiple subvoxel fibre directions from a diffusion MRI acquisition that has either (i) sparse diffusion encoding directions or (ii) low b values. It allows us to obtain more precise diffusion ODF estimates in each voxel using an acquisition that is otherwise optimized for single-tensor fitting. We compare the regularized diffusion ODFs to those obtained using q-ball reconstruction [1], and investigate the use of these regularized ODFs in fibre tractography.

Methods MRI data were acquired on a Siemens 3T Trio MR scanner (Siemens Medical Systems, Erlangen, Germany) using an 8-channel phased-array head coil. Diffusion encoding was achieved using a single-shot spin-echo echo planar sequence with twice-refocused balanced gradients. Two coregistered datasets were acquired, both with 99 diffusion encoding directions, 2mm isotropic voxel size, and 63 slices. The first dataset was acquired using a single-tensor optimized b value of 1000 s/mm², while the second was designed for q-ball reconstruction, using $b=3000$ s/mm² ($q=0.35$ μm^{-1}). A 1mm isotropic resolution T1 weighted anatomical scan was also acquired (TR=9.7ms, TE=4ms, $\alpha=12^\circ$). For the first dataset, the diffusion ODF, Ψ , given by $\Psi(\theta, \phi) = \int P(r, \theta, \phi) dr$, with P the diffusion probability density function, was calculated using the single diffusion tensor (DT) model [5]. For the second, the diffusion ODF was calculated using q-ball (QB) reconstruction [1]. Both ODFs were normalized to unit volume.

The regularization algorithm [4] was run on the diffusion tensor derived ODF field. The algorithm models fibre tracts locally as segments of 3D helix curves. This allows for curvature and torsion to vary along a tract. For each voxel (i), for each of N isotropic ODF sampling directions (\mathbf{u}), the average local support (s) was calculated by considering all pairs of voxels in a local neighbourhood of the voxel i . The average local support for direction \mathbf{u}_m at voxel i is given by $s(\mathbf{u}_{m,i}) = \sum_j \sum_k \sum_n \sum_p r_{ijk}(\mathbf{u}_m, \mathbf{u}_n, \mathbf{u}_p) \Psi_j(\mathbf{u}_m) \Psi_k(\mathbf{u}_p)$, where j and k are voxel indices that range over the local neighbourhood of voxel i ; n and p are direction indices that range from 1 to N , and $r_{ijk}(\mathbf{u}_m, \mathbf{u}_n, \mathbf{u}_p)$ is 1 if the three orientations $\mathbf{u}_m, \mathbf{u}_n, \mathbf{u}_p$ are cohelical at voxels i, j, k ($i \neq j \neq k$), respectively, and 0 if they are not. $\Psi_j(\mathbf{u}_m)$ is the ODF value in direction \mathbf{u}_m at voxel i . Local support for each ODF sampling direction was maximized using a relaxation labeling algorithm [6]. In this implementation, a neighbourhood of radius 8mm and $N=100$ ODF sampling directions were considered. The ODFs obtained from the regularized diffusion tensor (r-DT) and QB approaches were compared qualitatively in regions of partial volume averaging of large, known fibre pathways: the corpus callosum (cc) and cingulum (cg), the corticospinal tract (cst) and the cc, the superior longitudinal fasciculus (slf) and the cst, and the pontine crossing tract (pct) and the coricopontine tract (cpt).

Streamline fibre tractography was run using the DT ODF dataset and the r-DT ODF dataset. In the tensor case, the maximum of the diffusion ODF (the principal eigenvector) was calculated. In the r-DT case, all maxima of the ODF that rose more than $3\sigma/2$ above their intermediate minima, with σ the ODF standard deviation, were calculated. These maxima correspond to the tangents to the most likely curves (fibres) in the voxel. Tracking followed all maxima of the ODF that gave curves with radius of curvature 2mm or greater (directions that generated paths with higher curvature were assumed to be crossing fibres and were not followed). FACT integration was used, and all curves were initiated on a subvoxel grid of $3 \times 3 \times 3$ seed points per seed voxel in order to facilitate branching even with single-maximum ODFs.

Results

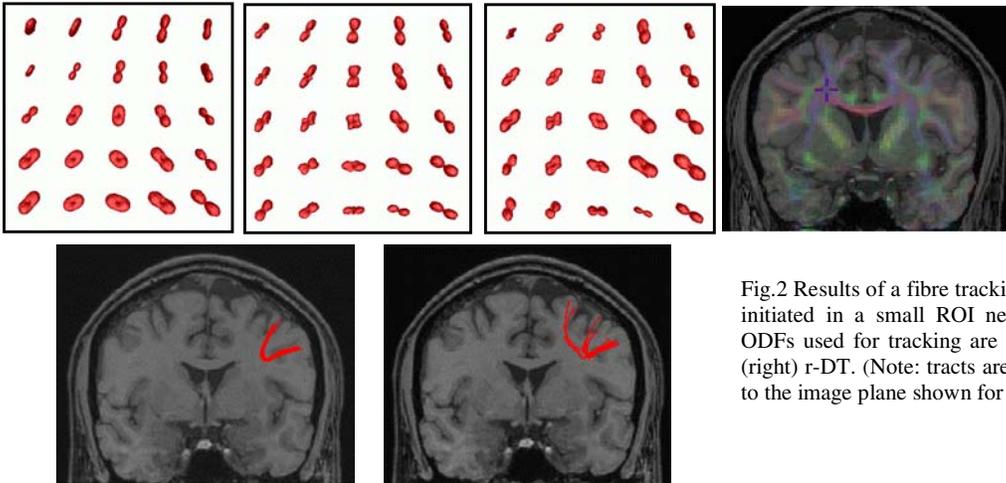


Fig.1. Diffusion ODFs obtained using (from left to right) DT, r-DT, and QB reconstructions in a region of partial volume averaging of cc and corona radiata (cr). The region of interest (ROI) is indicated by the crosshair in the rightmost figure, which shows the principal diffusion direction RGB map overlaid on the T1 weighted anatomical.

Fig.2 Results of a fibre tracking experiment initiated in a small ROI near the cortex. ODFs used for tracking are (left) DT, and (right) r-DT. (Note: tracts are not restricted to the image plane shown for reference.)

Discussion As illustrated in Fig.1, the r-DT and QB reconstructions indicated multiple fibre directions in the same regions. The DT ODFs are planar in the region of partial volume averaging of fibre directions, meaning a single, potentially incorrect maximum is calculated. The more precise ODF maxima obtained using the regularized ODFs can be expected to yield more precise tracking results. In Fig.2, the r-DT tracking result indicates more extensive cortico-cortical connections than does the DT tracking result. This can be explained by the increased incidence of branching made possible by the high angular resolution ODFs. The r-DT approach can be used to reconstruct multi-peaked ODFs where the single-tensor model would be inadequate. This is of particular value when acquiring diffusion weighted data in limited scanning times. We note that HARD reconstruction techniques can be used where time and gradient performance permit, and that the regularization is applicable to any ODF, making it suitable for regularization of HARD ODFs as well.

References [1] Tuch, D.S. *et al.* *Neuron* 40(5):885-895, 2003. [2] Tournier *et al.* *NeuroImage* 23(3):1176-85, 2004. [3] Campbell *et al.* *NeuroImage* 27(4):725-736, 2005. [4] Savadjiev *et al.* *LNCS* 3749:123-130, 2005. [5] Basser *et al.* *JMR* 103:247-254, 1994. [6] Hummel *et al.* *PAMI* 5:267-287, 1983.