Regularization of Diffusion Tensor Fields in Axonal Fibre Tracking

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Purpose

To develop and demonstrate effective noise reduction in Diffusion Tensor Imaging (DTI) by applying Markov Chain Monte Carlo (MCMC) techniques to the whole diffusion tensor [1].

Introduction

The integrity and course of white matter fibre tracts is of key importance in understanding the structural basis of functional integration of cortical centres in complex cognitive tasks, of the origin of functional impairment in focal brain lesions and finally the plasticity allowing functional reorganization after such lesions. Due to the inherent noise of MR diffusion measurements the direction and size of diffusion tensor may be inaccurate, leading to erroneous results in terms of the derived white matter fibre paths. Previous studies within regularization of DTI have been performed [2], with focus on regularization of the tensor principal eigenvector only. Here we present a novel regularization method using all information stored in the diffusion tensor. Considering the whole tensor can potentially improve the regularization in areas with low anisotropy due to e.g. crossing fibre bundles. We demonstrate it reduces the noise and thereby improves further data processing such as fibre tracking.

Methods

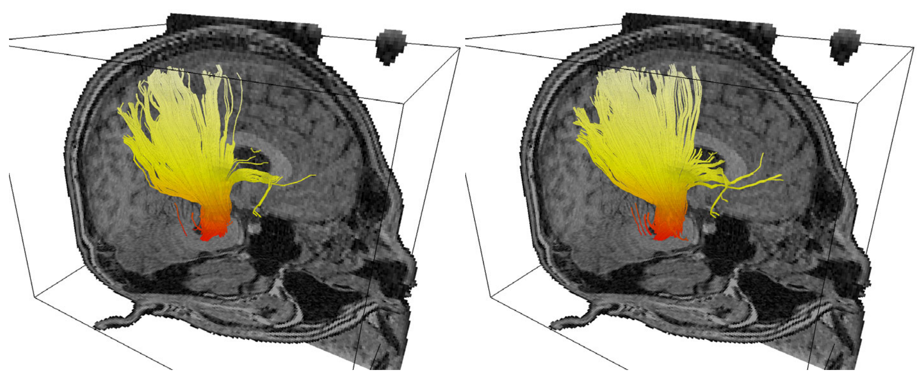
DTI was performed on a volunteer using a birdcage headcoil and 1.5 T GE Medical Systems scanner with a 40 mT/m gradient system. DTI was performed using single shot double spin echo EPI (DSE-EPI) due to it lower sensitivity to the eddy-currents [3]. The diffusion encoding scheme consisted of 17 different directions isotropically distributed in space, b-factor of 1000 s/mm^2. In addition, two b-factor=0 s/mm^2 images were acquired. This acquisition scheme has been shown to give rotationally invariant and unbiased diffusion data [4,5]. The maximum gradient strength was kept at 36 mT/m. 50 slices locations of slice thickness 3.30 mm were acquired, covering a 24 cm FOV in a 128 by 128 matrix. TR/TE = 17000/84 ms. A total of 4 replicated scans were performed, acquisition time was 22 minutes. T1-weighted imaging was also performed.

A Bayesian approach combines the observation model and the *a priori* knowledge (low curvature of axonal fibres) to give an *a posteriori* density. Simulating from the posterior density using MCMC methodology produces a regularized set of MRI tensors. The optimal field of tensors F is the field maximizing the a posteriori density: $p(F^*|F)=p(F|F^*)p(F^*)/p(F)$ where F* is the set of actual acquired apparent diffusion coefficients (ADC) for each diffusion direction. The *likelihood* density $p(F \mid F^*)$ is determined by the observation model, which depends on the actual data acquisition. The variability of the diffusion coefficient $F_w(u)$ measured at voxel w in direction u depends on the true value of the directional diffusion coefficient $f_w(u)$. Formally we have $\mathrm{Var}(F_w(u)|F^*)=h(f_w(u))$. Whether a particular choice of h is appropriate can be examined empirically. A general type of *prior distribution* is of Gibbs type.

Likelihood suggestion: $p(F \mid F^*) = \left[\prod_{w \in W} \prod_{i=1}^{k} \frac{1}{\sqrt{2\pi h(f_w(u_i))}} \right] \exp\left(-\frac{1}{2} \sum_{w \in W} \sum_{i=1}^{k} \frac{(F_w(u_i) - f_w(u_i))^2}{h(f_w(u_i))} \right)$. Prior suggestion: $p(F^*) = \frac{1}{Z} \exp(-\alpha \sum_{w \sim w'} d(f_w, f_{w'}))$

where ~ in the last equation is a neighborhood relation on W, Z is a normalizing constant and the function d measures the distance between the diffusion functions. The prior parameter α determines the "smoothness" of the regularization. In the MCMC algorithm each tensor is visited iteratively and a new tensor is proposed from the Wishart distribution (a multivariate analog to the chi-square). The proposed tensor is accepted with a probability depending on the degree of fit to the posterior density compared to the current tensor. Finally, the stopping criteria for the algorithm and the choice of α were optimized. After regularization, the eigensystem was calculated from the tensor in each voxel using diagonalization. The principal eigenvector is assumed to represent the local direction of an axonal fibre and fiber tracking is constructed by the FACT algorithm [6].

Results and discussion



The regularization method proved stable, converged rapidly while tested in human as well as synthetic data (a torus model resembling curving fibre bundles in isotropic tissue). Our test showed no tendency for the algorithm to "over-regularize", i.e. discard small fibre structures. The corticospinal tract is a large and well-described tract and is shown in the pictures. The left hand image shows the tracking result on unregularized data. The right hand image corresponds to the tracking after regularization. Note that even small fiber structures are preserved, and that the course of subcortical fibres is more realistically depicted in the regularized image. We have shown that regularizing the field of diffusion tensors provides an effective noise reduction in DTI data and preliminary results indicate that directional information even in smaller well-defined bundles are retained. Furthermore we believe this will be a valuable tool in the work of creating a gold standard for fibre tracking.

References

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