Multi-scale characterization of white matter tract geometry

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Introduction The geometry of white matter tracts is of increased interest for a variety of neuroscientific investigations, as it is a feature reflective of normal neurodevelopment and disease factors that may affect it. A large group of methods for white matter geometry analysis in diffusion MRI (e.g. [1]) compute the curvature and torsion of individual fibres recovered with a tractography algorithm. An elegant alternative was recently introduced on the basis of the currents framework, which represents fibre tracts as a smooth vector field and captures global tract shape [2]. All geometry analysis methods based on fibre tractography are inherently limited in that tractography does not, in general, produce stable and reproducible results. Recognizing this limitation, a method for computing white matter geometry indices directly from diffusion imaging data, without requiring prior tractography, was proposed in [3]. This method, however, is currently only defined for the single tensor model of diffusion, itself with well known limitations. Here we propose a novel scale-based white matter geometry analysis method that is situated logically between that of [3] and that of [2]. While our method is based on vector fields derived from tractography and is therefore subject to all associated limitations, its advantage with respect to [3] is that it is not limited by the tensor model of diffusion, and allows for a more precise characterisation of fibre fanning at different spatial scales. As for the method of [2], it is optimized to capture global tract shape and its modes of variation in a population. In contrast, our method computes local geometrical features based on the differential geometry of curve sets. We note, however, that our method is complementary to that of [2], and both may be used in conjunction in order to analyse the geometry of a currents vector field.

Theory Given a set $\mathcal{C}$ of curves C_i that represent the output of some tractography algorithm, with a tangent vector $\boldsymbol{T}$ defined at each point $\boldsymbol{p}$ along each curve, we compute at each $\boldsymbol{p}$ the function $\Psi(\theta) = \nabla_{\boldsymbol{v}}\boldsymbol{T}$, i.e, the covariant derivative of $\boldsymbol{T}$ in direction $\boldsymbol{v}$. Here $\boldsymbol{v}$ is defined as a direction on the unit circle centered at $\boldsymbol{p}$ in the plane orthogonal to $\boldsymbol{T}$, and is denoted by angle θ in that plane. In essence, $\Psi(\theta)$ can be thought of a "2D dispersion orientation distribution function (ODF)", since it measures along directions in the plane orthogonal to $\boldsymbol{T}$ the extent to which neighbouring fibres deviate from being parallel. Note $\Psi(\theta)$ is defined only for continuous vector fields, whereas our input is a discrete vector field constructed from the tangent vectors of 1D curves in 3D Euclidean space. To resolve this issue, we construct a continuous vector field at each location $(x,y,z) \in \boldsymbol{R}^3$ by simply averaging the discrete vector field over a neighborhood centered at (x,y,z). Since we seek to characterize the variation of curve orientation in directions orthogonal to the curves, we choose this neighborhood to be shaped as a *disk* lying in the plane orthogonal to $\boldsymbol{T}$, with a small thickness chosen to be 1 voxel. The radius S of this disk is then treated as a scale parameter.

Methods Diffusion-weighted images (DWI) were acquired from a volunteer on a 3T scanner (General Electric Company, Milwaukee, WI, USA) using an echo planar imaging (EPI) sequence, with a double echo option to reduce eddy-current related distortions. To reduce EPI spatial distortion, an 8 Channel coil and ASSET with a SENSE-factor of 2 were used. The acquisition consisted in 51 directions with b=900 s/mm^2, and 8 baseline images with b=0s/mm^2. The scan parameters were: TR=17000 ms, TE=78 ms, FOV=24 cm, 144 × 144 encoding steps, 1.7 mm slice thickness. A total of 85 axial slices covering the whole brain were acquired. We illustrate the method on fibre tracts connecting the substantia nigra in the brainstem to the striatum, obtained with a multi-fibre state-of-the-art tractography method [4]. The substantia nigra regions were manually outlined by an expert, and the striatum was automatically segmented using the FreeSurfer pipeline (http://surfer.nmr.mgh.harvard.edu/). This fibre tract was selected for illustration purposes because it presents a well-defined fanning structure. We compute $\Psi(\theta)$ at each $\boldsymbol{p}$ in this dataset, for a sampling of the unit circle in 20 directions at equally spaced intervals in θ. We computed $\Psi(\theta)$ at different spatial scales as described above.

Results For a simple visualization of the information contained in $\Psi(\theta)$, we color the fibre tracts by the average value of $\Psi(\theta)$ at each $\boldsymbol{p}$, which we refer to as the "average dispersion" at each point. We present results on the same fibre tract for five different spatial scales in Fig. 1. As expected, at the smallest scale only very local dispersion features are highlighted. With increasing scale, the central part of the fanning structure is highlighted more strongly, while small features are progressively lost.

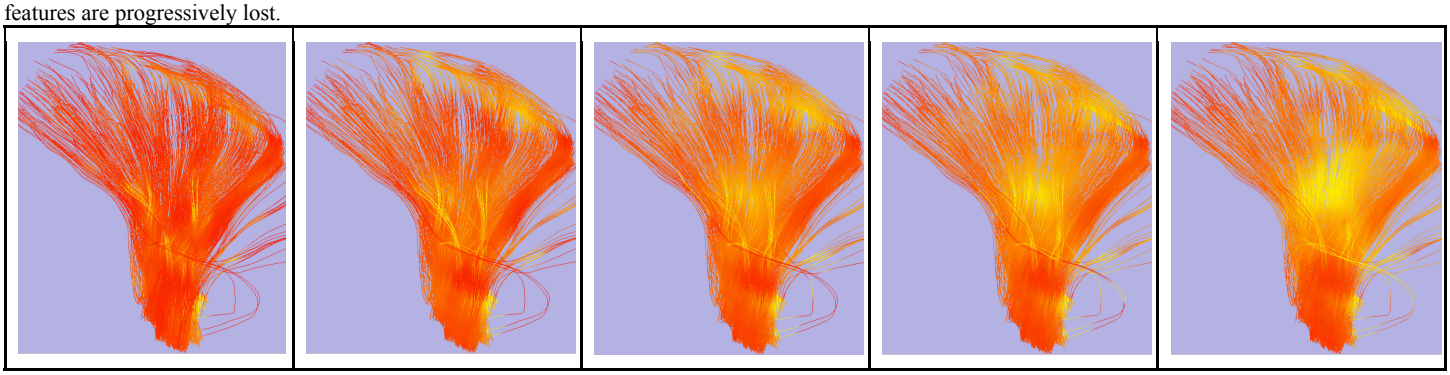

Figure 1. Fibre tracts connecting the substantia nigra in the brain stem to the striatum (a subcortical grey matter structure). The tracts are colored by "average dispersion" at each point, computed on the same fibre tract at different spatial scales. Yellow indicates higher values. From left to right: scale S= 1.7mm; 3.4mm; 5.1mm; 6.8mm; 10.2 mm.

Discussion We presented a multi-scale approach for computing white matter fibre geometry, based on the local differential geometry of curve sets. The method works with curves representing the output of a fibre tractography algorithm, and as such has both advantages and weaknesses. The main drawback of this method is its dependence on the tractography algorithm used to generate the input fibres. Acknowledging this limitation, we note, however, two important advantages of our method vs. a non-tractography-based method such as [3]. First, unlike the method of [3] our approach is not limited by the single tensor model of diffusion. It can be used in conjunction with any HARDI-based tractography to analyse tracts that go through fibre crossing regions. This type of tract geometry is not reflected by the single tensor model of diffusion. Second and more important, the fibre tracts provide an explicit correspondence between the white matter and locations on the cortical surface where they originate or terminate. This is very important if one is interested in studying the connection between white matter and grey matter geometry, which is part of our future work plans.

References [1] P. G. Batchelor *et al*. Quantification of the shape of fiber tracts. Magn Res Med 55:894–903, 2006. [2] Durrleman *et al*. Statistical models on sets of curves and surfaces based on currents. Medical Image Analysis 13(5):793–808, 2009. [3] Savadjiev *et al*. Local white matter geometry from diffusion tensor gradients. NeuroImage 49:3175-3186, 2010. [4] Malcolm *et al*. Filtered multi-tensor tractography. IEEE TMI 29:1664-1675, 2010.