A minimal model, data-driven approach to tractography

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Introduction: With advances in diffusion weighted MRI acquisition, many approaches to tractography have been developed to extract the likely positions of neural tracts.[1-3] It is desirable to attempt to reconstruct the true fibre orientation distribution function as this should provide the underlying fibre structure, however, this requires very large amounts of data and is not generally clinically applicable due to the long scan times. Considering the tractography algorithms for use with DTI data, which samples fewer directions, the general approach is to fit a model to the data and then use a tractography algorithm to extract the tracts. Fitting a model is inherently a reduction in information, and the results will obviously have a dependency on how well the model fits the data, the extent of which is not traceable from the end result. We have explored a tractography algorithm for use with DTI data which aims to use just the raw data to produce a map of structural connections in the brain.

Theory: If the data acquired in diffusion weighted MRI is considered as samples from a signal profile at each voxel, then the signal surface can be reconstructed by fitting spherical harmonics to the data.[4] The spherical harmonic coefficients are computed using a least squares minimization and the Stejskal-Tanner equation[5] is used to calculate the corresponding diffusivity profile; figure 1 shows an example of a diffusivity surface calculated from real data. The surface obtained allows interpolation of the measurements to calculate, for any direction, the signal intensity, and consequently the diffusivity, consistent with the data. The principle behind the tractography algorithms is to imitate the diffusion process that water molecules undergo in producing the diffusion weighted images in order to reconstruct the underlying fibre structure giving rise to these measurements. This involves seeding a number of particles at any given starting voxel, and allowing them to 'diffuse' through the image by sampling the local diffusion surface at each step. The Einstein diffusion relation[6] is used to relate the measured diffusion properties in a given direction to the mean particle displacement. Although strictly only valid for free diffusion, the diffusion relation is employed here to approximate the diffusion behaviour since the actual impediments to diffusion in a given voxel are likely to be location dependent and cannot be determined for most clinical datasets. An angle constraint is used between consecutive steps to ensure forward propagation of the path. At each step the direction is sampled randomly within the angle constraint and the corresponding displacement using constant time steps, or conversely, the time interval using equal displacements is calculated; both methods are considered here. The local diffusivity properties along the path can thus be sampled and used to calculate the mean speeds of the paths. Paths with a high mean speed correspond to the optimum routes for diffusion between regions, which are expected to be coincident with the underlying fibre pathways between regions, hence can be used to infer the likely structural connections in the brain. The approach allows tracking through regions of low anisotropy.

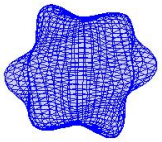

Fig.1: Diffusivity profile calculated from raw data points.

Methods: The two stepping approaches were both implemented and compared: The equal time step approach uses the local diffusion surface to determine the length of each step; however, tracking through low diffusivity regions or in low diffusivity directions requires many small steps which is computationally inefficient. To avoid this problem the surfaces were normalised to the mean diffusivity and the corresponding time steps calculated. This method will be referred to as the normalized distance varying step method (NDVS). The advantage of this method is that the distribution of steps in a voxel will resemble the diffusivity profile directly; hence if a step is taken in a low diffusivity direction in a voxel with high anisotropy, there is another opportunity to sample from this voxel and the possibility remains of sampling in the direction of high anisotropy. The second method tested here will be called the Time Variable Step (TVS) method, and this uses the height of the diffusion surface to give the time taken for a single step; here all step lengths are equal but the time of a step varies. The computational advantage of this method is that the image volume can be traversed more quickly as all steps move the particle by a voxel length. All paths are defined as starting and terminating in the grey matter, and must pass through white matter. Paths which leave the image boundary are removed. A phantom[7] was employed to test the performance of the tractography algorithms. The image size is 64x64x3 with 64 diffusion directions acquired at b=1500smm^{-2}. The highest order spherical harmonic function used was 1 less than the maximum to smooth the data and allow for noise.

Results: Examples for tracking the paths between regions are shown in figure 2. Both methods performed well on the phantom data and were able to extract the true paths between regions. The TVS method is superior in terms of computational efficiency.

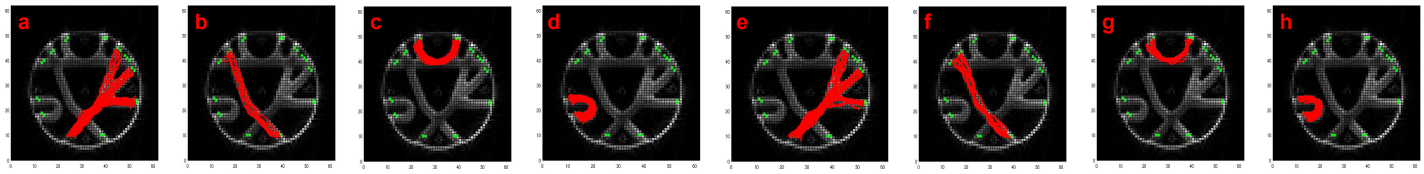

Fig 2: The perimeter of the phantom is defined as grey matter and inside as white matter. Starting voxels are shown in green. (a-d) Tracking results for region to region connectivity using TVS method; (e-h) Tracking results for region to region connectivity using NDVS method.

Discussion: The principle behind the methods is that no model is imposed on the data, hence the paths obtained are the results of a diffusion simulation using the measured diffusivity. The sampling for direction is random, hence a high number of paths are required to ensure the whole image is explored, and many uninformative paths are generated which do not contribute to the final result. Both methods are successful in elucidating the fibre structure between 2 specified regions as shown in figure 2. Currently a threshold is applied to extract the optimum paths as the strongest connections are represented by the paths with highest mean speed; a future aim is to use a connectivity matrix to assess the connection strength between regions. No assumption is made regarding the number of fibres or the fibre configuration in the voxel, the aim is to find the path between regions that is supported by the data, and consider the relative strength of connection compared to other regions.

References: [1] Tournier et al., NeuroImage 2004;23:1176; [2] Behrens et al. MRM 2003;50:1077; [3] Tuch et al., MRM 2004;52:1358; [4] Alexander et al., MRM 2002;48:331; [5] Stejskal & Tanner, J. Chem. Phys. 1965;42:288; [6] Einstein, Ann. Phys. 1905;17:549; [7] Poupon et al. MRM 2008;60:1276.