Towards assessing spatial normalizations employing DTI and HARDI models

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Background and Objective: Diffusion MRI offers a unique *in vivo* contrast into local white matter (WM) architecture. In the form of diffusion tensor imaging (DTI) it is now routinely included in research studies for diseases ranging from post traumatic stress disorder through schizophrenia as well as for clinical interpretation. Since the limitations of the tensor model have been observed, especially in the context of complex white matter architecture, a number of high angular resolution diffusion imaging (HARDI) models have been developed with improved sensitivity to multiple fiber populations within each voxel. This has prompted their use within population studies. The purpose of this work is to compare the utility of these contrast mechanisms (DTI and HARDI) for the procedure of spatial normalization, a crucial component of voxel based morphometry (VBM) studies. Specifically, HARDI and DTI imaging datasets were acquired on the same subjects; state of the art registration algorithms were then applied and compared.

Method: Our data consisted of DTI and HARDI datasets acquired from 27 healthy adolescent subjects (age 10.76 ± 2.35 years). DTI/HARDI datasets were acquired on Siemens 3T Verio™ scanner using a 32 channel head coil and a single shot spin-echo, echo-planar sequence with the following parameters: DTI: TR/TE=16900/70 ms, b-value of 1000 s/mm² and 30 gradient directions. HARDI datasets were acquired using the same sequence but with the following parameters: TR/TE=14.7s/110ms, b-value of 3000 s/mm², 64 gradient directions and 2 b0 images. Preprocessing consisted of eddy current correction as well as the removal of Rician noise [1]. Diffusion tensor models were then fit to the DTI data while fiber orientation distribution functions (FODs) were fit to the HARDI datasets using [2].

Registration Methods: All DTI images were then registered to the DTI image of a template subject using the DTIDroid [3] registration algorithm. The resultant deformation fields were then applied to the FOD images of that specific subject. Similarly the FOD registration algorithm, described in [4], was used to register the FOD images to that of the same template subject; these deformations were then applied to the DTI image of that subject. At the culmination of this process, each subject had 4 registered images: DTI images registered using both DTI and FOD methods and 2 FOD images, one from each registration method.

Comparisons: The goal of registration techniques is to determine the point-wise correspondence between subjects and, in doing so, to remove the component of population variance that is due to the misalignment of the subjects' anatomy. Three forms of population variance were utilized to evaluate the registrations. Fractional anisotropy (FA) measures the degree of anisotropic diffusion within a voxel using the DTI model. The FOD and nFOD variances are defined as $\frac{1}{n}\sum d(f,\bar{f})$, where f is each subject's FOD or normalized FOD (FOD normalized to have unit integral) and \bar{f} is the population average. While both FOD variances are sensitive to orientation and complexity of the underlying WM architecture, the normalized FOD variance highlights the orientation particularly in the cortical WM.

Results: Figure 1 shows population variances (FA, FOD and nFOD) computed on the two sets of registered images. Each variance image was smoothed using a 6mm FWHM Gaussian kernel to more accurately reflect the use of these variances within a statistical framework and to improve visualization. As is clearly shown, the HARDI based registration minimizes all three variance measures whereas the DTI based registration adequately minimizes only the FA variance.

Discussion: Within this work, we treat two diffusion models, DTI and FOD, as separate features of a subject's neuronal tissue and compare the utility of the supplied contrasts for determining the spatial correspondence between subjects. Implicit in this approach is the assumption that a single deformation between two subjects should exist that aligns both types of images. In this case meeting this assumption is quite realistic since the same imaging sequences were used for both acquisitions in the same scanning session. As is evident from examining figure 1, the HARDI based FOD registration method is able to achieve a comparable FA variance to that

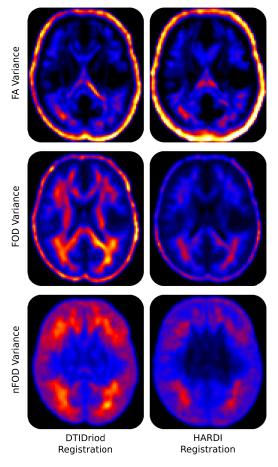


Figure 1: HARDI registration outperforms the DTIDroid registration technique when using either of the FOD based variances as a measure of comparison. When using FA variance to compare the registration methods both perform similarly.

obtained using the DTI based registration method, while outperforming the DTIDroid registration results using either of the FOD based variances as a means for comparison. This suggests the registration algorithm that utilizes the contrast obtained from the HARDI acquisitions was able to outperform those that use the more typical DTI acquisitions, making HARDI a better choice when accurate registration is required for voxel based morphometry studies.

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