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MINIMIZATION MODELS FOR HARDI DATA DENOISING

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Introduction: Diffusion imaging is a relatively new and powerful method to measure the 3D profile of water diffusion in the brain. These images can be used to reconstruct fiber directions and pathways in the living brain, providing detailed maps of fiber integrity and connectivity. HARDI (High Angular Resolution Diffusion Imaging) is a powerful new extension of diffusion MRI, introduced in [2,3,4,7], and which goes beyond the diffusion tensor imaging model. HARDI intensity is given at every voxel and at any direction on the sphere. It allows computation of the orientation diffusion function over a sphere of possible directions. The first HARDI acquisition and processing methods were developed in [9,10], and later [1] used spherical harmonic expansions for processing HARDI data sets. HARDI data is highly contaminated with noise for larger *b*-values (parameter pre-selected to collect data). We wish to denoise HARDI data arising in medical imaging of the brain, a necessary step before mapping cerebral connectivity through fiber tractography.

Methods: We formulated two computational minimization models to denoise HARDI data. The first (I) directly denoises the collected data S, while the second (II) denoises *d=sADC* (spherical Apparent Diffusion Coefficient), a field of radial functions derived from the data. These two quantities are related by an equation of the form $S = S_0 \exp(-b \cdot sADC) + noise$ at every voxel and direction. The vectorial total variation regularization [8] has been used combined with L^1 data fidelity terms. Our model (I) imposes the constraints that *S* must be positive and with values smaller than S_0, while our second model (II) imposes the positivity constraint on *d* (using the logarithmic barrier).

Results: We tested the proposed methods on real HARDI datasets with 94 diffusion-sensitized gradient directions. We used the data as in [5]. 3D structural brain MRI scans and DT-MRI scans were acquired from healthy young adults on a 4 Tesla Bruker Medspec MRI scanner using optimized diffusion tensor sequence. Imaging parameters are TE/TR 92.3/8250ms, 55x2mm contiguous slices, FOV=23cm. 105 directional gradients were applied: 11 baseline images with no diffusion sensitization (i.e., T2-weighted images) and 94 diffusion-weighted images (*b*-value 1159 s/mm^2) in which gradient directions were evenly distributed on the hemisphere. The reconstruction matrix was 128 x 128, yielding a 1.8x1.8mm2 in-plane resolution. Total scan time was 14.5 minutes. We set S_0 to be the average of the 11 baseline images. Figure 1 shows one slice of the data (through ODFs) and denoising results. We notice that the structure is well preserved, while the noise is removed.

Conclusions: Denoising HARDI data is a necessary step before registration of HARDI data to an atlas, or before the reconstruction of fibers in the brain. We have proposed two different computational models for denoising HARDI data. From our experiments, both models produce satisfactory results. However, we think that the second model better takes into account the degradation model. Also, although we do not explicitely model the noise as Rician noise (the correct, but more difficult way to model noise in MRI data), the computed noise obtained by our model (II) has a distribution very close to the Rician distribution.

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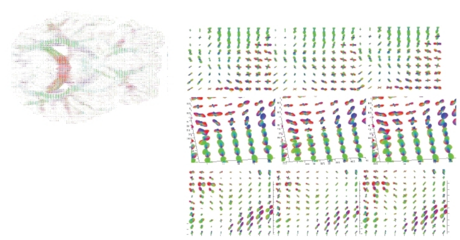

Figure 1: Left: ODF: 19th slice of brain data. Right: each column, left to right, ODFs of: noisy data, denoised result using model (I), denoised result using model (II).