Splines on the Sphere Q-Ball Imaging

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Introduction Q-Ball imaging (QBI) (1) was proposed as a high angular resolution diffusion imaging (HARDI) technique to elucidate areas with intravoxel white matter heterogeneity. Of the HARDI orientation distribution function (ODF) reconstruction algorithms presented previously (2-6), QBI stands out due to its linearity and model independence. Although originally formulated using the spherical radial basis functions (sRBFs), spherical harmonics were later used in a modified reformulation of QBI (7, 8). Spherical harmonics were also used in a recent work (9) to model the raw HARDI data with a basis that incorporates a regularization term defined on the unit sphere. All spherical harmonics based QBI techniques require a truncation of the expansion above a certain order. We present here an alternative reconstruction algorithm to QBI that first models the HARDI data using smoothing splines on the sphere that are subsequently used for QBI reconstruction and compare it with the original QBI reconstruction algorithm based on sRBFs. Acquiring high b-value diffusion-weighted images (DWIs) result in images with even lower SNR than the conventionally used DWIs. An initial smoothing of the HARDI data in the diffusion gradient space is therefore desirable and the splines on the sphere method achieves this. A direct application of the Funk-Radon transform (FRT) to the splined diffusion signal gives the q-ball ODF. Monte Carlo noise simulation results and *in vivo* HARDI human brain data are presented to validate our new approach to QBI.

Methods For data residing on the sphere like diffusion-weighted intensities, smoothing splines on the sphere are natural manifolds for these types of data. The splines on the sphere algorithm estimates the diffusion-weighted signal as a smooth function by penalized least-squares in a reproducing kernel Hilbert space (10). The estimated spline is defined everywhere in 3D diffusion space from the original sampled data. The FRT in QBI can be applied by directly interrogating the spline for the equator points diffusion-weighted signals perpendicular to the final reconstruction directions as in the FRT formulation. It is important to note that unlike in the original q-ball algorithm, no re-gridding of the signal from the original sampling to spherical radial basis function centers is needed.

Monte Carlo Noise Simulations Voxels with two fiber populations in slow Gaussian exchange were simulated for two crossing scenarios, 90° crossing and 60° crossing. Each prolate tensor was assigned 0.5 volume fraction, fractional anisotropy 0.8, trace 2.1 x 10^{-3} mm^2/s and the diffusion-weighted data were estimated along 252 icosahedral-based directions on the sphere with b = 4000 s/mm^2 and added Rician noise (11) to achieve an SNR=20 in the diffusion-free signal over 1000 noise trials.

In Vivo Human Brain Data HARDI data were acquired from a normal consenting volunteer on a Siemens 3T Tim whole body MR scanner employing a diffusion-weighted single-shot EPI sequence in the coronal orientation. The data were acquired using a 12 channel volume coil along 256 directions uniformly distributed using an electrostatic charge repulsion method on the northern hemisphere with b-value = 4000 s/mm^2 and imaging parameters: TR/TE = 3000/129ms, NEX = 1, FOV = 200 mm x 200 mm, matrix size of 96 x 96, resolution of 2.1 x 2.1 mm^2, 5 mm slice thickness with parallel imaging (GRAPPA) acceleration factor of 2.

QBI reconstruction for the simulated data employed a Gaussian sRBF interpolation kernel width, σ_i , of 8°, and Gaussian smoothing kernel width, σ_s, of 1° whereas for the *in vivo* data, σ_i was 11° and σ_s was 3°. In both cases, the q-ball ODF was reconstructed on 642 directions from a tessellated icosahedron. For the human brain data set the 256 sampling directions were mirrored into the southern hemisphere. For the Splines on the Sphere QBI (S^{2}QBI) reconstruction, a penalizing smoothing parameter, λ, of 10^{-5} was used for both simulated and *in vivo* data and 642 directions were used for ODF reconstruction. All ODFs were MinMax normalized as in (1).

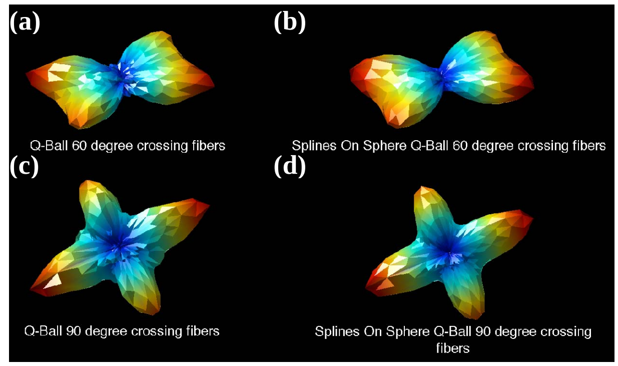


Fig. 1 Examples of simulated noisy QBI and Splines on the Sphere QBI (S^{2}QBI) MinMax orientation distribution functions (ODFs) for 60° (a), and (b), and for 90° (c), and (d), crossing fibers, respectively. The effect of noise is more evident in the QBI ODF reconstructions as compared to the S^{2}QBI ODFs.

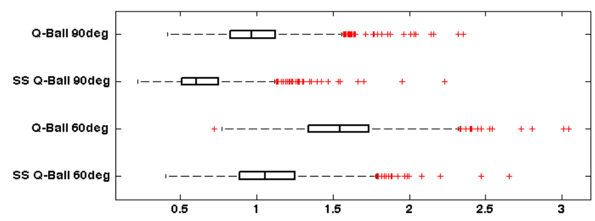
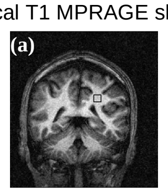


Fig. 2 Mean bias between simulated noisy and ground truth ODFs for QBI and S^{2}QBI for the 90° crossing case, upper two box plots, and the 60° case, lower two box plots. The S^{2}QBI ODFs exhibit less bias than their QBI counterparts.

Results & Discussion Splines on the sphere modeling of HARDI data is very natural considering that the data resides on a sphere. For high b-value HARDI data, noisier diffusion-weighted data results prompting a smoothing that needs to be done not in the slice image space but in the diffusion signal space. The splines on the sphere algorithm achieves that noise reduction and estimates the spline in the entire 3D diffusion space. Fig. 1 shows qualitatively how less noisy the S^{2}QBI ODFs are in relation to the QBI ODFs for the 60° and 90° crossing cases with significantly less mean bias for the S^{2}QBI ODFs over the QBI ODFs for both crossing situations as is shown in fig. 2. As expected the bias is less in the 90° crossing case for both ODF reconstructions as compared to the 60° case. Fig. 3 shows an anatomical T1 MPRAGE slice image with an ROI in white matter marked in black. The ROI captures a region of fiber crossings between the splenium of the corpus callosum, optic radiation, arcuate fasciculus, and possibly the tapetum. The S^{2}QBI ODFs are clearly smoother with better defined peaks assisting in tractography applications.



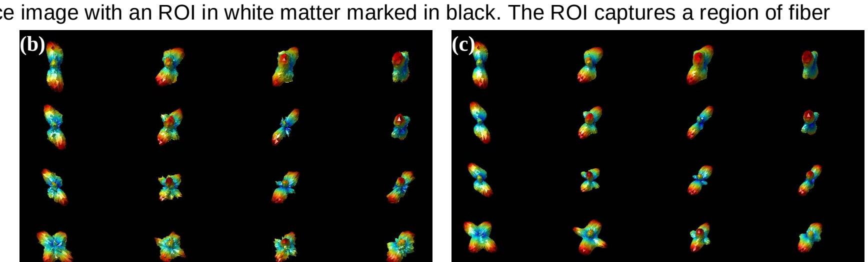


Fig. 3 (a) T1 image with ROI marked, (b) QBI ODFs, and (c) S^{2}QBI ODFs. The S^{2}QBI ODFs are clearly smoother with better defined peaks.

Conclusion We have presented the splines on the sphere method of modeling the raw HARDI data with the added feature of smoothing of the diffusion data in the 3D diffusion space. Extending that to QBI, with S^{2}QBI, the resultant ODFs are of better quality than their QBI counterparts without compromising angular directionality which will be beneficial in fiber tracking applications.

References 1. Tuch DS, *Magn. Reson. Med.,* 2004 (52):1358-1372. 2. Frank LR, *Magn. Reson. Med.,* 2002 (47):1083-1099. 3. Alexander DC *et al.*, *Magn. Reson. Med.,* 2002 (48):331-340. 4. Tuch DS *et al.*, *Magn. Reson. Med.,* 2002 (48):577-582. 5. Özarslan E *et al.*, *Magn. Reson. Med.,* 2003 (50): 955-965. 6. Tournier J-D *et al.*, *Neuroimage,* 2004 (23):1176-1185. 7. Hess CP *et al., Proc. ISMRM* 2005:389. 8. Anderson AW, *Magn. Reson. Med.,* 2005 (54):1194-1206. 9. Descoteaux M *et al.*, *Magn. Reson. Med.,* 2007 (58): 497-510. 10. Wahba G, *J. Sci. Stat. Comput.*, 1981(2):5-16. 11. Jones DK, *Magn. Reson. Med.*, 51:807-815, 2004.