

Diffomorphic Image Registration of Diffusion MRI Using Spherical Harmonics

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INTRODUCTION: Nonlinear registration of diffusion MRI is crucial for group analyses and for building a white matter and fiber tract atlas. Most current diffusion MRI registration techniques [1-2] are limited to the alignment of diffusion tensor imaging (DTI) data. Here we propose a novel diffeomorphic registration method for diffusion images by mapping their orientation distribution functions (ODFs). ODFs can be reconstructed using q-ball imaging (QBI) techniques [3] and represented by spherical harmonics (SHs) to resolve intravoxel fiber crossings. The registration is based on optimizing a diffeomorphic demons cost function. Unlike scalar images, deforming ODF maps requires ODF reorientation to maintain the consistency with the local fiber orientations. Our method simultaneously reorients the ODFs by computing a Wigner rotation matrix at each voxel, and applies it on the SH coefficients during registration. Rotations on the coefficients avoid the estimation of principle directions, which has no analytical solution and is time consuming. The performance of the proposed method was tested using different SH orders. Results show that registration with higher orders (2nd-order is equivalent to tensor models [4]) improves the performance in terms of smaller similarity error and higher directional consistency.

METHODS: Theory: The ODF, $F(\mathbf{u})$, reconstructed by a great circle integration on the sphere of the diffusion-attenuated signal in q-space [3], can be represented as a linear combination of a set of real SH basis with order l and phase factor m (Eq.(1)), using only even orders due to the antipodal symmetry. The invariant shape distance between two ODFs can be defined as the Euclidean distance between their coefficients (Eq.(2)). A 3D rotation can be decomposed to three Euler angles using z-y-z convention (Eq.(3)). The real SH coefficients can be rotated in a similar way as vectors with Wigner matrices (Eq.(4)) [5]. The registration was stated as an optimization problem of finding spatial transformation h_{12} that minimizes a cost function defined in Eq.(5). The rotation was extracted from the inverse of the local Jacobian of h_{12} as in Eq.(6). h_{12} was initialized to identity and the velocity field v_{12} was initialized to zeros and updated iteratively by gradient decent optimization. The updated v_{12} was composed to h_{12} to obtain the updated transformation.

$$F(\mathbf{u}) = \sum_{l=0, \text{even}}^L \sum_{m=-l}^l c_{lm}^l Y_{lm}(\mathbf{u}) \quad (1)$$

$$D(F_1, F_2) = \|F_1 - F_2\| = \sqrt{\sum_{l=0, \text{even}}^L \sum_{m=-l}^l |c_{lm}^1 - c_{lm}^2|^2} \quad (2)$$

$$R = R_z(\alpha_3) R_y(\alpha_2) R_z(\alpha_1) \quad (3)$$

$$\mathbf{R}(F(\mathbf{u})) = \sum_m \sum_{l=0, \text{even}}^L \lambda_{lm}^l Y_{lm}(\mathbf{u}) \quad \text{where} \quad (4)$$

$$\lambda_{lm}^l(\alpha_1, \alpha_2, \alpha_3) = \sum_{m'=-l}^l R_{mm'}^l(\alpha_1, \alpha_2, \alpha_3) c_{lm'}^l \quad (4)$$

$$C = D(R_z(F_1(h_{12})), F_2) + \sigma \text{dist}(v_{12}) + \rho \text{Reg} v_{12} \circ h_{12} \quad (5)$$

$$\mathbf{R}_{12} = ((J(h_{12}) \cdot J(h_2)^T)^{-1/2} J(h_{12}))^T \quad (6)$$

Data acquisition: Human brain QBI data from five healthy subjects were acquired at a 3T Siemens scanner. Each subject was scanned twice. Isotropic axial images were obtained using a single-shot diffusion spin-echo EPI sequence with TR/TE=8s/114 ms, FOV=195mm, matrix=78x78, yielding a 2.5mm image resolution. 162 diffusion encoding directions with a b-value of 3000 s/mm² and one reference image were acquired. 48 slices with slice thickness=2.5mm were obtained to cover the whole brain. The total scan time was approximately 26 minutes.

Experimental design: Three mixture zero-mean Gaussian diffusion tensors were simulated with SNR=100 using "Camino" [6] to validate the rotation along y, z-axes. A 25° z-rotation of a real QBI data with and without ODF reorientation was simulated to demonstrate the necessity of ODF reorientation during spatial alignment. To test the proposed method, two metrics, generalized fractional anisotropy (gFA) [7] and directional consistency (DC) were computed after affine and the proposed method with different orders of SHs. DC was defined by the cosine value of the rotation angle that minimizes two spherical shapes.

RESULTS & DISCUSSION: Fig.1(a-d) illustrate the ODF reorientation by rotating coefficients with simulated 3-tensor data sets and (e-f) demonstrate that ODF reorientation ensures the consistency with rotated fiber orientations. Fig.2 shows that diffeomorphic registration aligns the macro structure of the target image to the reference more accurately compared to affine registration; registration with higher orders maintains fiber crossings and results in more precise ODF alignments. Fig.3 plots histograms of the normalized standard deviation of gFA and the average DC after diffeomorphic registration with different SH orders. With higher orders, gFA had smaller standard deviation and DC had values closer to 1, indicating less shape similarity error and higher directional consistency. Tab.1 summarizes the two measures for intra-subjects, and affine and diffeomorphic registrations of inter-subjects. The diffeomorphic registration with higher SH orders produced values closer to the intra-subject case.

CONCLUSIONS: We have developed a novel diffeomorphic diffusion MRI registration method by aligning the SH coefficients of their ODF maps. ODF reorientation was done by applying rotation matrices over the coefficients. Higher order SH registration provides better registration performance compared to 2nd order SH registration comparable to current available DTI registration techniques.

REFERENCES: 1. Alexander et al., IEEE TMI, 2001. 2. Zhang et al., IEEE TMI, 2007. 3. Hess et al. MRM, 2006. 4. Barmpoutis et al., MICCAI, 2007. 5. Geng et al., IPMI 2009. 6. Cook et al., ISMRM, 2006. 7. Tuch, MRM, 2007.

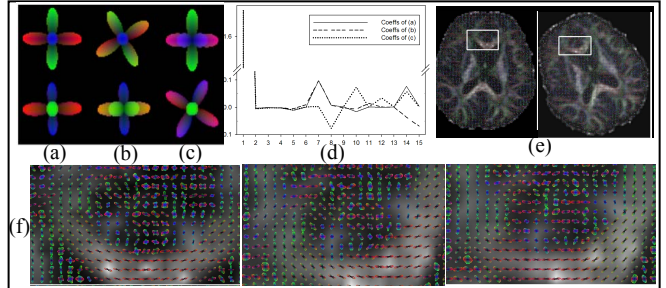


Fig.1. Illustration of the ODF reorientation with simulated 3-tensor data sets (a-d) and real QBI data (e-f). (a) A simulated 3-tensor ODF; (b) & (c) rotated ODF along z & y-axis, (d) SH coefficients of the three ODFs; (e) original and rotated ODFs; (f) enlarged ODFs of the original data (left panel), rotated data without & with reorientation (middle & right panel).

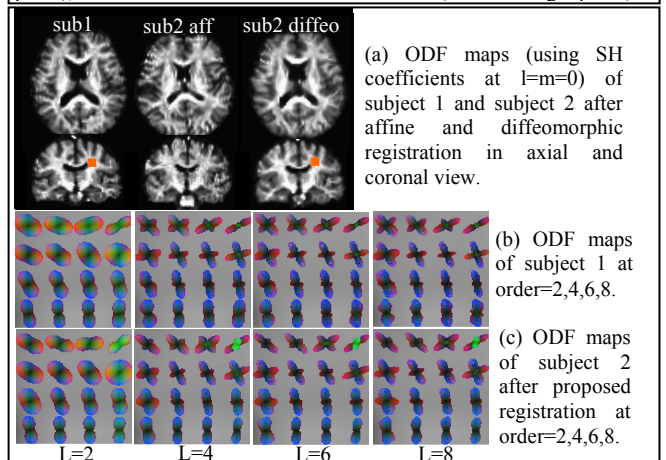


Fig.2. Representative registration results after affine and diffeomorphic aligning subject 2 to 1.

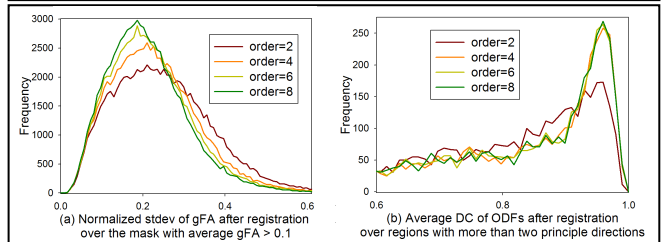


Fig.3. Comparison of diffeomorphic ODF registrations using SH coefficients with different orders.

	Intra-subject	Inter-subject affine registration				Inter-subject diffeomorphic registration			
		order=2	order=4	order=6	order=8	order=2	order=4	order=6	order=8
norm stdev gFA	0.145	0.3371	0.3114	0.2963	0.2851	0.2539	0.2337	0.2234	0.2157
average DC	0.9123	0.6965	0.7064	0.7074	0.7062	0.7841	0.7991	0.7996	0.8001

Tab.1. Normalized standard deviation of gFA and average DC in intra-subject (affine align the data in the 2nd session to the 1st), inter-subject affine registration and diffeomorphic registration with different orders of SHs.