Featured based Deformable Registration of Diffusion MRI using the Fiber Orientation Distribution

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Introduction: Higher order diffusion models (HOMs), have been gaining popularity within the diffusion imaging community due to their ability to model complex white matter which cannot be accurately modeled by DTI. In order to facilitate subsequent group based statistical studies, the diffusion data must be registered to a common coordinate frame, a task complicated by the high dimensionality and orientational nature of HOMs. We present a method for spatial normalization of diffusion data fitted using the fiber orientation distribution function [1] (FOD) as the diffusion model. The method uses rotationally invariant features in conjunction with a multichannel demons algorithm and is one of the few methods that address the challenging problem of spatial normalization of higher order model data.

Materials and Methods: Our approach is to first compute voxel-wise rotationally invariant features of the template and moving FOD images and utilize a multichannel demons algorithm to perform registration in this feature space. The final transformation is then applied to the moving image using a finite-strain based scheme to reorient the FOD at each voxel.

FOD Estimation: The DWI signal is expressed as the spherical convolution of the fiber response function, the DWI signal for a single fiber bundle oriented along the z axis, and the FOD [1]. We estimated the response function by first performing a DTI analysis and extracting the signal profile from voxels with a fractional anisotropy greater 0.7.

Rotation Invariant Features: The FOD is a real-valued spherical function and can be expressed in the basis of real spherical harmonic (RSH) functions, indexed by order, l, and phase, m. When rotating a spherical function, the rotation operation will shift energy within the phase coefficients (m) but not from one order (l) to another. Thus the energy within each order of the FOD's RSH expansion is rotationally-invariant. Given an FOD image, $I(x)$, we can compute the energy within an order l is $I_l(x) = \sum_{m=-l}^{l} (I_{l,m}(x))^2$ and build a series of rotationally invariant feature maps, one for each order, to use for registration.

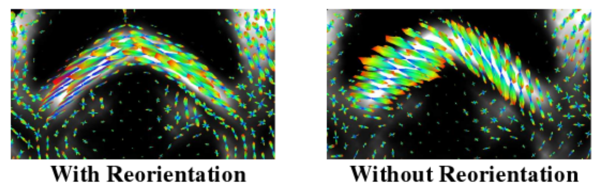

Fig 1: Images of the posterior corpus callosum, with and without finite-strain reorientation of the fiber orientation distributions (FODs) following a 45 degree rotation. Note that without reorientation the principle directions of the FODs do not coincide with the underlying anatomy.

FOD Registration: We first compute the representation of template and moving image in a rotationally invariant feature space. We then utilize a multichannel demons algorithm [2, 3] to perform registration in this feature space. The diffeomorphic demons algorithm consists of iteratively minimizing an energy functional of the form $E(u) = \sum_p \left\| F(p) - M \circ \exp(u(p)) \right\|^2$. At each iteration the update takes the form of $\exp(u)$, where $u(p) = (J_p^T J_p + (\frac{\sigma_i}{\sigma_x})^2 Id)^{-1} J_p^T (F(p) - M \circ s(p))$, where J_p is the negative jacobian of the deformation field at p and $M \circ s(p)$ is the deformed moving image from the previous iteration. Additionally, the update field is smoothed at each iteration to achieve a smooth spatial transform.

The final transformation is then applied to the moving image using a finite-strain based scheme to reorient the FOD at each voxel. We utilize the finite strain algorithm [4] to estimate the rotational component (R) of the transform based on its jacobian at a particular voxel. The FOD (f), at each voxel is then replaced by $f' = f \circ R^{-1}$. In the RSH representation this takes the form $f' = Wf$, where W is the RSH Wigner matrix [5] equivalent, corresponding to R^{-1}.

Results: We validate our registration framework on HARDI data from 8 healthy adult subjects, acquired using a spin-echo, echo-planar imaging sequence, TE 85 ms, TR 6.4 s, 1.73x1.73x2 mm voxels, b = 1000 s/mm^2 on a Siemens 3T Tim Trio Scanner. Each dataset consisted of 64 diffusion weighted images and 6 unweighted images. An FOD image of order 8 (45 components) was computed using the CSD method. A template image was chosen from the group of subjects and an affine transformation was computed between the template's b=0 image and each subjects b=0 image. This transformation was then applied, with reorientation, to each subject's FOD image. The affinely registered FOD image was then used as the input into the registration process described above.

In order to evaluate our registration framework, error maps (using the L2 metric in the RSH vectorspace) were computed for each subject. These error maps were then averaged yielding a single scalar map (similar to variance maps for scalar registration) which could be examined in order to determine spatial locations which were poorly registered. The average error maps for the affine and registered results can be seen in figure 2. A clear improvement can be seen in all white matter areas, although regions surrounding the splenium of the corpus callosum show higher error values. We suspect that this error may be improved by acquiring data at higher b-value although that is left to future work.

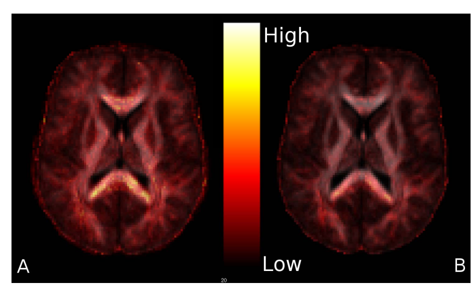

Fig 2: The average registration error from the mean FOD image to each registered subject, using affine registration (A) and multichannel demons (B).

Conclusion: We have provided a method of spatially normalizing diffusion data fitted with higher order models, using a feature-based Demons algorithm. The method has been validated on real data and has shown low registration error.

References:

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