Registration of High Order Diffusion Tensor Imaging Based On Apparent Diffusion Coefficients

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Introduction:

In DT images, second order tensor is usually used to represent Gaussian diffusion of water molecules in human brain. The accuracy of DT registration can be increased by using similarity metric of full tensor or combined components[1]. However, second order tensor is incapable to resolve multiple fiber orientations within a voxel, which in theory would affect the accuracy of image alignment. In order to better describe the complexity of diffusion, diffusion imaging with a high number of gradient directions (HARDI) has been proposed. One method to model the HARDI[2] diffusion is using spherical harmonics (SH) representation as $D(\mathbf{g}) = \sum_{l=0}^{n-1} \sum_{m=-l}^{l} \lambda_l^m Y_l^m(\mathbf{g})$, where $\mathbf{g}$ is a gradient direction and $D(\mathbf{g})$ is the apparent diffusion coefficient (ADC) on the direction, Y_l^m are the real SH (which are convertible to complex SH). It is known that functions represented by SH can be rotated by a linear transformation of the coefficients. Ivanic[3] has introduced a recurrent procedure that could be derived for constructing the rotation matrices between real spherical harmonics directly in terms of the elements of the original 3x3 rotation matrix. Using SH representation and its rotational feature, two similarity metrics of ADC profile for the DTI registration could be directly derived.

Methods:

A global affine registration is first performed to have initial alignment. To compute the affine transformation, SPM program was used to register the corresponding T1 images. The elastic matching algorithm[4] computes a local match described by a displacement field over one image. The algorithm proceeds by iteratively finding a solution to a partial different equation which balances between the smoothing of the deformation and the external force that is derived from local similarity metric of the images.

Metric 1: rotational variant measure

A mean square distance of the ADC over a unit sphere could be easily computed by SH coefficients at each point i.

$E_i = \iint_\Omega (R(g) - T(\mathbf{M_i} \cdot g))^2 d\Omega = \sum_{l=0}^{n} \sum_{m=-l}^{l} (R_l^m(x_i) - Tnew_l^m(x_i - u_i))^2$, $\mathbf{Tnew}(x_i) = \mathbf{R_{sh}}(M_i) \cdot \mathbf{T}(x_i)$, Where $\mathbf{R_{sh}}$ is the matrix for the coefficients transformation within each band. Similar to the tensor reorientation, $\mathbf{M_i}$ is a local rotation estimation of the deformed local frame using finite strain algorithm[5]. It should be considered that there is an issue about how the high order ADC profile is changed by deformation field, currently in this paper a simple strategy is used, which assumes the shape of diffusion is kept and only the local frame is rotated[5].

Metric 2: rotational invariant measure

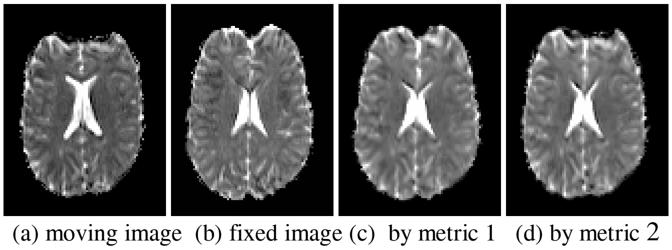
For spherical harmonic coefficients, the energy of each band is rotational invariant which can simply for the metric computation without the SH matrix. $E_i = \sum_{l=0}^{n} (\sum_m R_l^{m2}(x_i) - \sum_m T_l^{m2}(x_i - u_i))$.

Results:

A single pair of brain DT images is used. Images were acquired on a 3.0T Simens machine and 60 gradient directions were sampled. The DW images were resampled to an iso-voxel resolution of 2mm. The spherical harmonics coefficients were then estimated by a linear regression for the 60 direction to the order of 6 which has 3 even bands with 15 coefficients. 20 iteration steps were preformed on both metrics. The slices of the first coefficients maps at the same z index are shown in the figure. A slight misregistration could be observed for metric 2.

Conclusions:

In general, the similarity metrics using SH coefficients for high order diffusion tensor imaging are derived directly from the ADC profile which are more sensitive to the registration. The registration by metric 1 using SH rotation matrix obtains accurate alignment. However, even for high order tensor, the registration by metric 2 produces less accuracy. However, metric 1 has the performance cost for computation of the local SH rotation matrix from the deformation field on each voxel, which takes much part of time within one iteration.



(a) moving image (b) fixed image (c) by metric 1 (d) by metric 2

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