

A Comparative Study of Diffusion Tensor Field Transformations

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Background & Objective: Diffusion tensor (DT) magnetic resonance imaging is unique in its ability to non-invasively visualize the white matter fiber tracts in human brain in vivo. MR diffusion is based on microscopic diffusion of water molecules which is a truly three dimensional process. A symmetric second rank tensor is often used as a model for characterizing the diffusion. Diffusion tensors contains orientational information that is affected by the transforms applied during image registration. Therefore, this directional information needs to be correctly rotated such that the tensors are consistent with the tissue reorientation caused by application of the resulting transformations. Previous work carried out in this area concentrates on reorientation of tensors by different methods. Xu et al (2003) have used the transformation and fiber direction estimate to reorient the tensors. Alexander et al (2001) have implemented the preservation of principle direction method. We have addressed this problem with a novel technique where the rotation is applied to the diffusion sensitizing gradients providing a voxel by voxel estimate of the diffusion gradients instead of a volume of by volume estimate. We have compared our technique with an existing method where the transformation is applied to the resulting diffusion tensors. In both the methods, rotation is computed from the deformation field by decomposing the local linear transformation.

Methods: A single subject underwent a multi-modality imaging study to obtain anatomical T1 and T2 images using a 1.5T scanner. DTI data was acquired on a 3T Siemens Trio scanner using 20 directions of diffusion encoding and a b-value of 1000. The following parameters were used to obtain the diffusion tensor images: TR/TE=6100/123.252 ms, matrix=128x128, FOV=220x220mm, slice thickness/gap=3.0/0.0mm. Registration was performed to warp the diffusion tensor data to the atlas space defined by the MNI atlas. For this work, a multi-stage approach was employed. First the B0 image was co-registered to the T1 weighted image using a rigid transform and a mutual information metric. This was followed by a B-Spline registration between the T1 image and the MNI atlas image after skull stripping both image sets. The resulting transform is defined by a deformation field. According to the polar decomposition theorem, a non-singular deformation gradient tensor, $\mathbf{F} = \mathbf{I} + \mathbf{u}\nabla$, where $\mathbf{u}\nabla \equiv \frac{\partial \mathbf{u}_i}{\partial x_k}$, can be decomposed into the finite strain parameters of rotation and strain tensors (Alexander, 2001). We used singular value decomposition (SVD) to obtain the rotation tensor component. The cumulative effect from rigid body rotation combined with the local deformation was represented by multiplication of two successive rotation matrices, $\mathbf{R}^{\text{rigid}}$ and $\mathbf{R}^{\text{deform}}$. The local diffusion gradient vector was estimated at each voxel using $\mathbf{g}_i = \mathbf{R}_i^{\text{deform}} \cdot \mathbf{R}_i^{\text{rigid}} \cdot \mathbf{g}$, where \mathbf{g} denotes uncorrected diffusion gradient vectors and corrected local gradient vectors of \mathbf{g}_i . In the second method, the rotated tensor was computed using the following equation: $D' = RDR^T$. Where D' is the rotated tensor and D is the original tensor. Both algorithms were generalized to support any affine transform supported by ITK and deformable registration represented by a deformation field.

Results: Figure 1 shows the primary eigenvectors that result after applying the Thirion-Demons transform initialized with a rigid body transform for the gradient rotation method (A) and the tensor rotation method (B). The results show that the average FA value measured within the white matter from the gradient reorientation is nearly identical to the tensor reorientation. The difference was less than 1% within the white matter region used for this analysis. The tensor interpolation used a first order approximation to the tensor interpolation solution. Higher order solutions are possible using Riemannian geometry (Fletcher et al, 2004) providing a better estimate of the ellipsoid while increasing the computational complexity of the tensor interpolation. The gradient reorientation required only a standard scalar linear interpolation. The diffusion gradient reorientation also gains from the fact that it can be directly applied to other representations of the underlying fiber architecture such as Q-ball imaging (QBI) that can be gathered from high angular resolution diffusion data (HARDI).

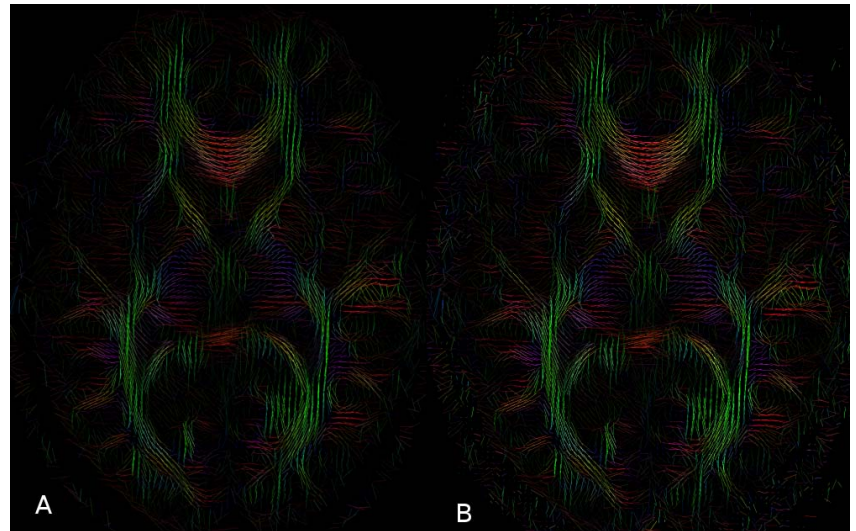


Figure 1. Primary eigenvector shown for gradient rotation method (A) and tensor orientation method (B)

Discussion: We have implemented an innovative technique of rotating the gradients that operates on the diffusion tensor data before tensor estimation while preserving the tensor direction after warping. Gradient rotation eliminates the problem of tensor interpolation and can be applied to other representations of fiber architecture. Since the tensor estimation is nonlinear, subtle differences may exist between the two methods. We have shown that the FA values are similar between these two techniques within white matter regions. The algorithms for both the methods are generalized such that any linear or non-linear transform can be applied.

References: Xu D et al., Magnetic Resonance in Medicine 50:175-182, 2003.
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