METHODS FOR REORIENTING AND RETRANSFORMING DIFFUSION WEIGHTED IMAGING DATA

T. Dhollander[1,2], W. Van Hecke[1,3], F. Maes[1,2], S. Sunaert[1,3], and P. Suetens[1,2]
[1]Medical Imaging Research Center (MIRC), K.U.Leuven, Leuven, Belgium, [2]Department of Electrical Engineering (ESAT), K.U.Leuven, Leuven, Belgium, [3]Department of Radiology, University Hospitals of the K.U.Leuven, Leuven, Belgium

Purpose

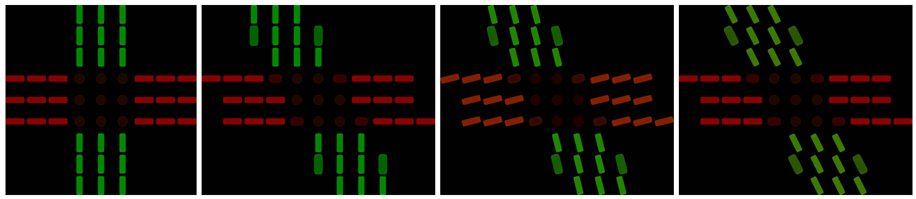
Spatially transforming diffusion weighted imaging (DWI) data poses a challenge, since the information in every voxel is dependent on the angular structure of the underlying tissue. A simple example clarifies the need to perform an extra reorientation step after interpolation. In **Fig. 1a**, a tensor image depicting a fiber crossing is shown. In **Fig. 1b**, a shearing is applied by interpolation only. The orientation of the tensors of the vertical fiber bundle clearly no longer agrees with the underlying sheared structure. We will now review different reorientation strategies, starting from the basic methods that operate on the tensor from diffusion tensor imaging (DTI) and building up to full fiber orientation distribution function (fODF) retransformation and methods that work on the raw data in q-space.

Outline of Content

In case of a rigid transformation, the problem is easy to solve: just ignore the displacement and scaling, and apply the rigid rotation directly to the data or model in each voxel. For the most difficult case of a non-rigid deformation field, the Jacobian matrix can provide a local affine model for each voxel. Therefore, the focus is on affine transformations. We will illustrate the outcome of a shearing on an artificial dataset of a simple fiber crossing.

Tensor reorientation

To preserve the properties of the tissue, the tensor should only undergo rigid rotation [1]. Two major strategies have been proposed to yield the rigid rotation matrix: finite strain (FS) and preservation of principle direction (PPD). In FS, the rigid rotation component of the affine transformation matrix is extracted and applied to rigidly reorient the tensor. The result (**Fig. 1c**) doesn't fully meet our expectations because the deformation component of the affine transformation didn't contribute to the estimated reorientation. The PPD algorithm solves this problem by constructing a rigid rotation that preserves the orientation of the first eigenvector, as well as the plane spanned by the first and second eigenvector. This illustrates the fact that the expected rigid rotation is dependent on the orientation of the underlying tensor in each voxel. The result of applying PPD is shown in **Fig. 1d**.

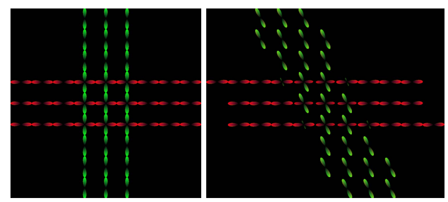


(a) **(b)** **(c)** **(d)**

Fig. 1. Tensor reorientation: **(a)** a crossing is **(b)** sheared with no reorientation, **(c)** FS, **(d)** PPD

Fiber orientation distribution function retransformation

Where the tensor model meets its limitations, the fODF yields information about more complex fiber populations (such as crossings) in each voxel (**Fig. 2a**). Because a single fiber orientation is no longer assumed, a more advanced fODF retransformation can be performed. Both [2] and [3] propose methods that are based on the same idea: applying the affine transformation to the orientations while preserving volume fractions of the fODF (because the fODF is a probability distribution function). While both methods to accomplish this are different, the results should theoretically be similar. The outcome of such a method is shown in **Fig. 2b**. In [2], the solution is obtained from a discretely sampled fODF. In [3], the fODF is represented by a weighted sum of spherical harmonics (SH) delta functions. The local affine transformation is then applied to the directions of the main axis of these SH delta functions, but the weights are preserved.

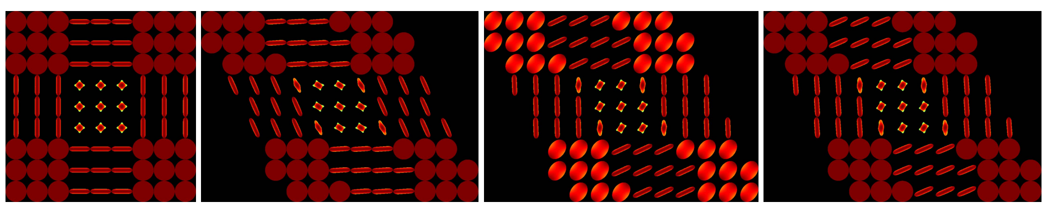


(a) **(b)**

Fig. 2. fODF retransformation: **(a)** a crossing is **(b)** sheared while preserving volume fractions

Q-space signal function retransformation

The raw data in q-space are actually (discretely sampled) signal functions on a sphere that take on larger values in directions perpendicular to the local fiber orientations (**Fig. 3a**). The gradient directions are the sampling directions, while the image intensities (normalized by a non-diffusion weighted image) are the samples. Some have suggested (such as in [4] and [5]) to just apply the affine transformation matrix directly to the gradient directions. However, as shown in **Fig. 3b** and explained in [6], this results in signal functions that are highly inconsistent with the transformed fiber orientations. A partial solution is to use the inverse transpose of the affine transformation matrix. In [6] a full solution is also constructed, building on the method of [3]. The straight translation of [3] to q-space yields a result as shown in **Fig. 3c**. By adding an extra isotropic volume fraction to the model, a more correct result can be obtained: **Fig. 3d** illustrates that this fixes the incorrect orientations of **Fig. 3b** and better preserves the qualities of isotropic regions (as compared to **Fig. 3c**). In [6], it is also reasoned that the methods of [3] and [6] can be seen as a natural extension of PPD.



(a) **(b)** **(c)** **(d)**

Fig. 3. Q-space signal function retransformation: **(a)** a crossing is **(b)** sheared by applying the affine transformation matrix directly to the gradient directions, **(c)** by preservation of anisotropic volume fractions, **(d)** by preservation of anisotropic and isotropic volume fractions

Summary

We have reviewed different methods to perform the reorientation or retransformation step that is necessary when spatially transforming images containing DWI data. From this short overview, the need for reorientation methods as well as the complexity of the problem and some pitfalls should be clear.

References

[1] Alexander DC et al.: Spatial Transformations of Diffusion Tensor Magnetic Resonance Images. IEEE TMI 20(11), 1131-1139 (2001)
[2] Hong X et al.: Spatial Normalization of the Fiber Orientation Distribution Based on HARDI Data. MRM 61(6), 1520-1527 (2009)
[3] Raffelt D et al.: Non-Linear Spatial Normalization of HARDI Data using Fiber Orientation Distributions. MICCAI 12, DMFC Workshop (2009)
[4] Tao X et al.: A Method for Registering Diffusion Weighted Magnetic Resonance Images. MICCAI 9(2), 594-602 (2006)
[5] Yap PT et al.: Non-Parametric Deformable Registration of High Angular Resolution Diffusion Data using Diffusion Profile Statistics. ISMRM 18, 3968 (2010)
[6] Dhollander T et al.: Spatial Transformations of High Angular Resolution Diffusion Imaging Data in Q-space. MICCAI 13, CDMRI Workshop, 73-83 (2010)