

DTI Atlas building process

Materials

The DTI process was carried out based on 50 datasets. Some imaging parameters include Repetition time (TR) of 11.4 sec and Echo time (TE) of 128ms with a voxel size of 2x2x2.75 mm. The b-value considered for all the datasets is 2500 with 61 gradient directions.

Preprocessing of DTI volume

Echo-planar Imaging (EPI) is typically used to acquire diffusion tensor (DT) images. So, these images are prone to Eddy current and head motion artifacts and susceptibility artifacts. To correct diffusion images for eddy current and motion artifacts, mutual information-based registration technique proposed by Rohde *et al* [1] is used. To overcome susceptibility artifacts distortion, an image-conserving image registration method proposed by Tao *et al* [2] has been used. This correction is done by optimizing the intensity differences between the Jacobian corrected EPI baseline images and the corresponding T2-weighted structural image.

DTI Atlas building

The rationale behind atlas building is to map all the DTI images into a common coordinate system to perform statistical analysis of diffusion parameters across all the datasets. The complete atlas building process explained below is based on software tools developed at University of Utah [3].

The pipeline first estimates the individual tensors and their respective scalar invariant measures (for eg. Fractional Anisotropy, FA) for each subject dataset. This processing is done using tools developed by DTIProcess project of NeuroLib. The atlas building procedure consists of three stages. The next stage entails the atlas construction from the set of patient or subject images. This is a multistep process of initializing the set of transformations to a template and then iterating to obtain an unbiased template or atlas within the space of diffeomorphisms between images, using the method of Joshi *et al* [3]. The results after affine registration are illustrated in Fig. 1. This atlas-building process jointly estimates an atlas or template image along with the set of diffeomorphic (invertible) mappings that provide spatial transformation between atlas image and every individual dataset.

The registration procedure within the atlas building step aligns a derived structural operator, namely maximum curvature FA, is used instead of FA itself. The operator is defined as the maximum eigenvalue of the Hessian of FA image. The Hessian serves as a computational approach for finding the direction of the maximum ridge response. So, it acts as a good detector for fiber bundles as can be seen in Fig 2.

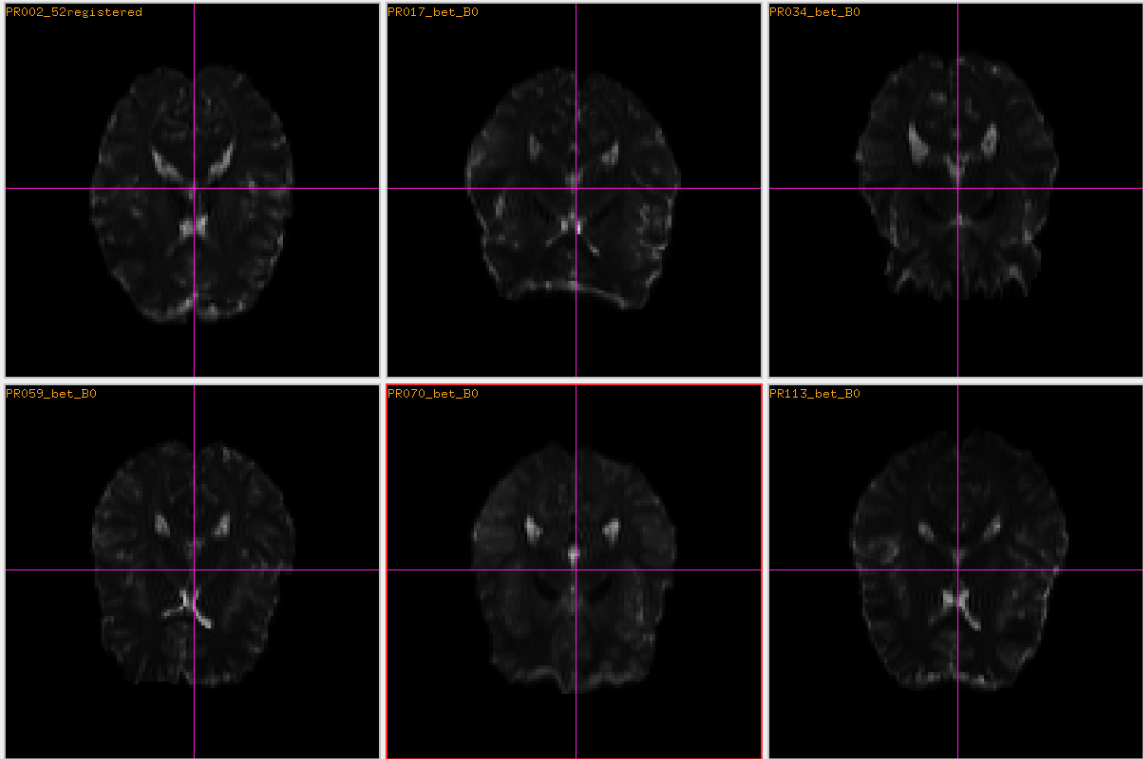


Fig. 1a. Before affine registration (random baseline images picked out of 50 datasets)

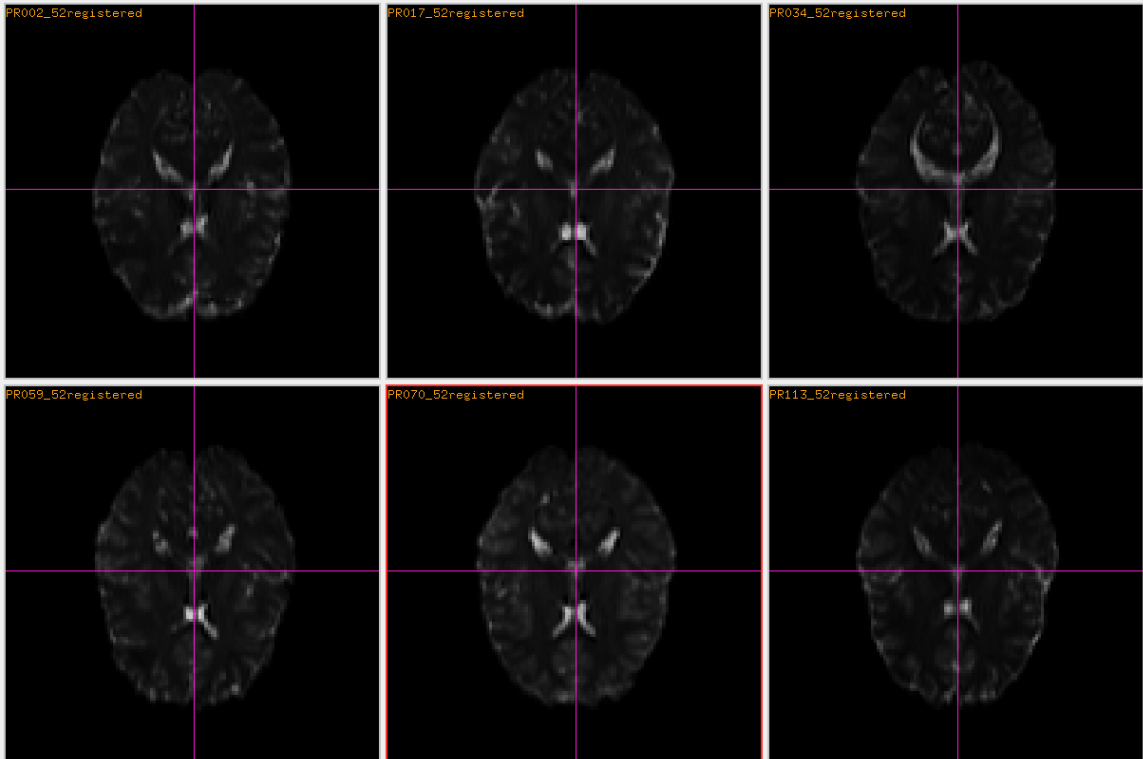


Fig 1b. After affine registration

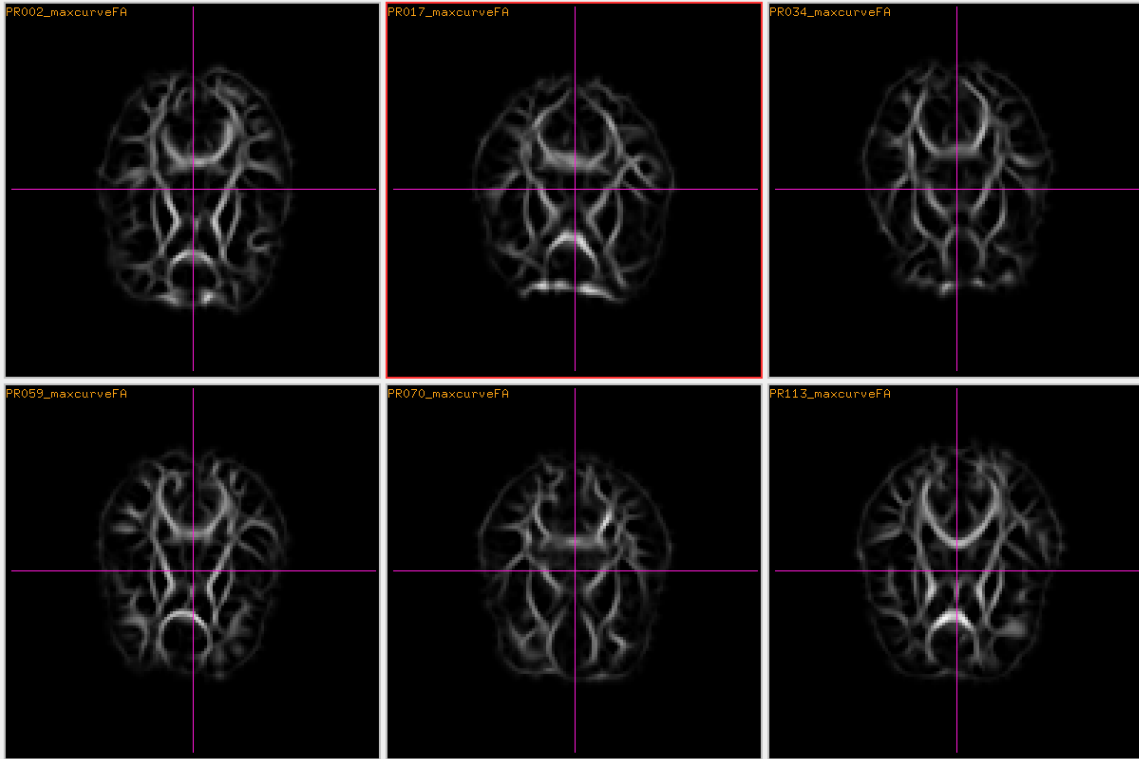


Fig 2a. Randomly selected Maximum curvature FA images before non-rigid registration

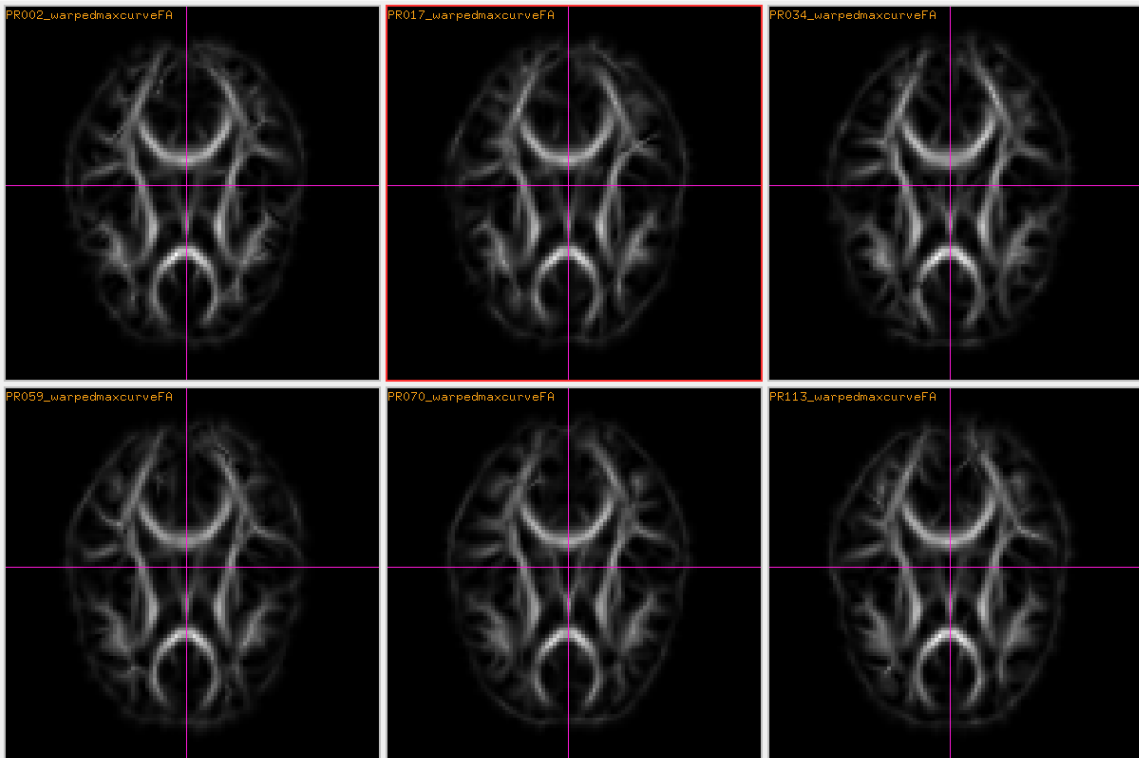


Fig 2b. Corresponding Maximum curvature FA images after non-rigid registration

To maintain the relationship between anatomy of the warped diffusion images and tensor orientation, the Riemannian framework has been used to reorient tensors relative to the

anatomical location. This framework restricts operations to remain in the valid space of symmetric positive-definite matrices [33, 34]. Once all the tensor volumes are deformed with locally rotated tensors, they are averaged using the Log-Euclidean scheme to produce the atlas tensor volume.

To create template fiber tracts from the atlas tensor volume, streamline integration method based on the fourth order Range-Kutta integration of the FA measure is applied. The fibers tracked using the above process is shown in Fig 3. The complete Atlas building procedure has been reviewed as a flowchart in Fig.4. Specified regions are manually selected to input prior anatomical knowledge into the segmentation of fiber bundles. Once the atlas fiber tracts are generated, diffusion properties are mapped from individual datasets to the template tracts. This results in individual fiber tracts possessing same geometry as in a template atlas tract but replacing the diffusion properties corresponding to the each dataset. Finally, statistical analysis is performed by comparing individual tracts with same geometry but varying diffusion properties.

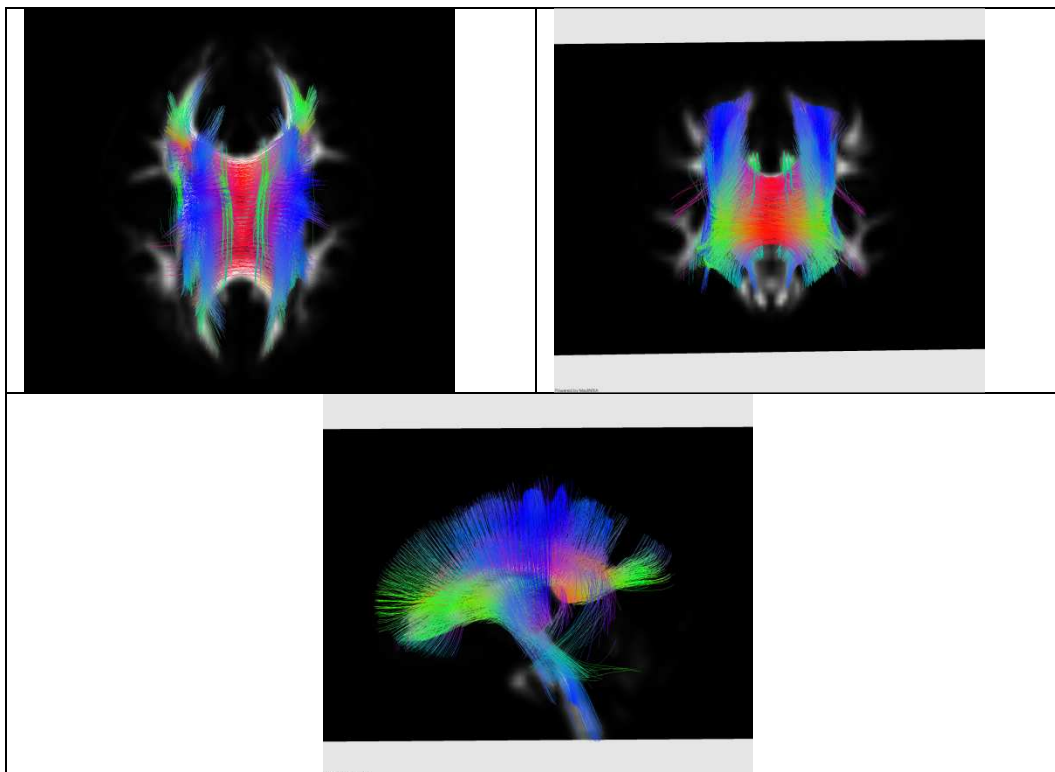


Fig 3: Fibers tracked on the Atlas image; Top row: Axial and Coronal view, Bottom row: Sagittal view

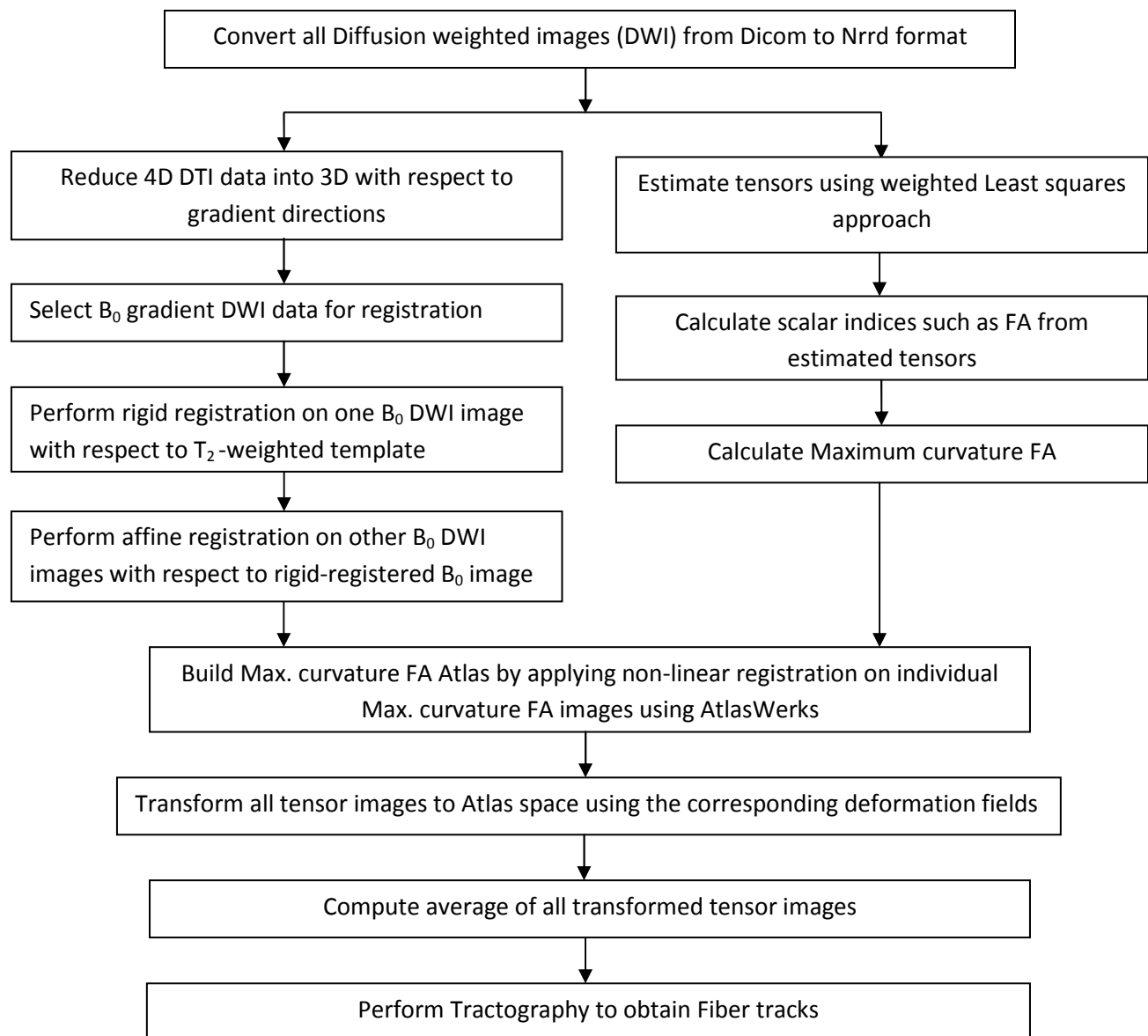


Fig 4. Flowchart of Atlas building process

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[2] R Tao, P T Fletcher, S Gerber, R Whitaker: A Variational Image-Based Approach to the Correction of Susceptibility Artifacts in the Alignment of Diffusion Weighted and Structural MRI. *IPMI 5636*, 664-675 (2009)

[3] C Goodlet: Computation of Statistics for Populations of Diffusion Tensor Images. PhD Thesis (2009)

[4] Joshi, S., Davis, B., Jomier, M., and Gerig, G. Unbiased diffeomorphic atlas construction for computational anatomy. *NeuroImage* 23, Supplement 1, 151-160 (2004).

[5] Fletcher, P., and Joshi, S.: Principal geodesic analysis on symmetric spaces: Statistics of diffusion tensors, *ECCV*, 87-98 (2004).

[6] Fletcher, P. T., and Joshi, S.: Riemannian geometry for the statistical analysis of diffusion tensor data. *Signal Processing* 87, Issue 2, 250-262 (2007).