An image registration based approach for establishing a normal white matter atlas using diffusion tensor imaging

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Introduction

DTI is capable of revealing white matter tracts in the brain with its sensitivity to directional water diffusion. After the seminary work of Basser (4), most efforts in the analysis of DTI images have concentrated on the implementations of approaches for fiber tracking to depict white matter network. However, the current inability to compare fiber tracking results across subjects has motivated several groups to look into how DTI images can be co-registered.

Alexander et al performed the first DTI registration work (1). The similarities of T1 images in combination with the trace of DT matrices were used as the cost function for elastic registration. In addition, Ruiz-Alzola, et al proposed a sum of squared difference (SSD) based framework for DTI registration (5). Subsequently, Alexander et al further introduced several tensor reorientation schemes taking into account the directional properties of DT matrices along with co-registration (2). Their most recent work employed an affine transformation for DT registration (3) and Jones et al have utilized this approach to build a DT template (6). In addition, Xue et al have developed a statistical tensor reorientation scheme after the anatomical images (T1) are registered (6). The major limitations associated with these approaches are either the tensor reorientation and registration are two separate steps (5, 6) or the transformation used for registration is of less flexibility (3). We propose an approach which simultaneously co-register both FA (can also be anotomical images) and diffusion matrices. Specifically, two 3D B-spline models are utilized for bi-directional transformation between the data pair. The cost function includes both the SSD on eigen-values and FA maps, the weighted directional inconsistency of the largest two eigenvectors between DT matrices, the regularization terms of the forward and backward transformations, and the inconsistencies between them. With the proposed approach, the tensor reorientation is naturally incooporated into the cost function and allows a direct construction of the mean DT templates.

Algorithm

Two 3D B-spline models M_1 and M_2 are used for characterizing the forward (from the source to the target) and backward (from the target to the source) transformations. The cost functions employed for registration are:

$$f_{1}(M_{1},M_{2}) = \sum_{k \in S} (I_{t}(M_{1}(\overset{p}{S})) - I_{s}(\overset{p}{S})^{2} + \sum_{l \in T} (I_{s}(M_{2}(\overset{p}{t})) - I_{t}(\overset{p}{t}))^{2} f_{2}(M_{1},M_{2}) = \sum_{k \in S} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{s,i}(\overset{p}{S})^{2} + \sum_{l \in T} \sum_{i=1}^{3} (\lambda_{s,i}(M_{2}(\overset{p}{t})) - \lambda_{i,i}(\overset{p}{t}))^{2} f_{2}(M_{1},M_{2}) = \sum_{k \in S} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{t}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{t}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(M_{1}(\overset{p}{S})) - \lambda_{i,i}(\overset{p}{s}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(\overset{p}{S}) - \lambda_{i,i}(\overset{p}{S}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(\overset{p}{S}) - \lambda_{i,i}(\overset{p}{S}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(\overset{p}{S}) - \lambda_{i,i}(\overset{p}{S}))^{2} + \sum_{l \in T} w_{s}^{2} \sum_{i=1}^{3} (\lambda_{i,i}(\overset{p}{S}) - \lambda_{i,i}(\overset{p}{S}))^{2} + \sum_{l \in T} w$$

 ξ and ξ are a voxel inside the source S and target T, respectively. I_s and I_t are the FA values of source and target data sets. $\lambda_{s,i}$ and $\lambda_{t,i}$ are the ith eigen-values of the source and target set. $p_{s,i}^{\rho}$ and $p_{t,i}^{\rho}$ are the ith eigen-vectors of the source and target sets. f_1 is the SSD of FA maps (can also be applied to anatomical images). f_2 is the SSD on the three eigen-values of the DT matrices. f_3 is to be minimized to align the two eigen-vectors corresponding to the two largest eigen-values, and the summation is weighted by the FA value at a voxel $\left(\begin{array}{c} w_{\frac{\alpha}{2}, w_{\frac{\alpha}{2}}} \end{array} \right)$ in combination with their eigen-values. f_4 is the consistent constraint to make sure one voxel can return to its original location after forward and backward, or backward and forward transformation pair. f_5 is a regularization constraint, which is the first order smoothess of the two transformations. Tensor reorientation is performed by finding the rotation matrix which approximates the local deformation matrix (obtainable everywhere within the volume of interest with the 3D B-spline model) through the Procrustean estimation. Thus, by minimizing the weighted sum of the cost functions listed above, the forward and backward registration can be determined simultaneously.

$$(M_1^*, M_2^*) = \arg\min(wt_1f_1 + wt_2f_2 + wt_3f_3 + wt_4f_4 + wt_5f_5)$$

Materials and Methods

10 healthy volunteers were recruited and written consent was obtained from each subject. DTI images were acquired by using a single shot EPI sequence with six directions of diffusion gradients from a head-only 3T MR scanner (Allegra, Siemens). The imaging parameters were as follows: b=1000 s/mm²; TR/TE=7000/82 ms; and voxel size =2*2*2 mm³.

Results

The figure on the left shows the overlapping of the principal eigen-vectors of the target (in red) and the reoriented source eigen-vectors (in green) from two subjects (with large geometrical difference) in three views. The mean FA maps and standard deviation are shown on the middle and right pannel respectively. In mean FA maps, major white matter regions are enhanced with the improved SNR. Our approach also demonstrates a low variance in subcortical region.



Discussion

An approach to register 3D DTI data directly, without the reqirements of anatomical images is proposed. The registration is bi-directional, which allows the mean images to be computed using both the source and target as the template. By using 3D B-spline models for transformation, more flexibility for image deformation can be achieved than the affine based registration methods. The mean and standard deviation of the computed DT templates can potentially be used in the future for identifying subtle DT changes in patients as well as allowing a direct comparion of fiber directions across subjects.

References

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