Template estimation for a group of DSI datasets using LDDMM

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Introduction: Spatial transformation of brain images is usually an important preprocessing step in neuroimage studies. The general scenario is to register each individual subject's image to a 'template' image or a 'mean' image, and then perform, for instance, inter-subject comparison, brain structure identification. The template images that are widely used include the MNI, ICBM, etc. While these template images are constructed based on another group of images, sometimes it is more preferable to use the template image which is generated intrinsically from the studying group. Although several methods have been introduced to construct the group-specific template image for 3D structural images [1, 2], to our best knowledge, no method has been proposed yet to address this issue for diffusion spectrum imaging (DSI) [3] datasets. Previously we suggested a way to spatially transform the DSI datasets using the large deformation diffeomorphic metric mapping (LDDMM) method [4]. One of the important properties of the LDDMM framework is that the transformation flow can be completely encoded in the initial momentum [5]. Consequently the 'mean' image of a group of images can be defined as the one where the sum of the initial momentums from the mean image to each of the images in the group vanishes. In the present article we demonstrated a method to iteratively estimate the template from a group of DSI datasets.

Materials and Methods: DSI datasets of 102 points in q-space with b-values up to 4000 s/mm^2 were acquired from seventy healthy subjects on a 3T MRI scanner (Tim Trio, Siemens). Other imaging parameters were: TR/TE = 9600/130 ms, matrix size = 80×80×56, voxel size = 2.5×2.5×2.5 mm^3. In order to minimize the translational and rotational differences among the DSI datasets to facilitate template estimation, the b0 image of each DSI dataset was rigidly registered to the MNI template using SPM 8 so that the DSI datasets would all approximately aligned in the MNI space. Parameters of the LDDMM DSI algorithm [4] are: time steps = 10, smoothing (alpha) = 0.01, smoothing (gamma) = 1.0, integration of velocity field to generate deformation maps used the semi-Lagrangian method. Given the initial DSI template $DSI^{(1)}_{template}$ be the average of all aligned DSI datasets (DSI_i, $i=1...N$), for k=1 to K, the following procedure iterated:

(1) For each DSI dataset, applying the LDDMM DSI algorithm [4] to $DSI^{(k)}_{template}$ and DSI_i, which would result in the initial momentum $Mom^{(k)}_i$ and the deformation $Def^{(k)}_i$.

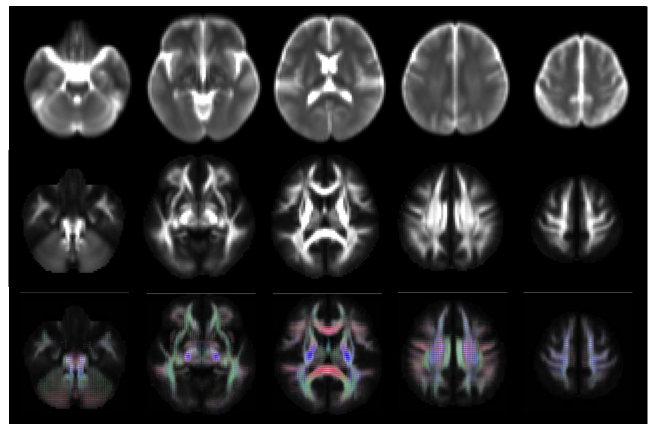

Figure 1

(2) The residual momentum $ResMom^{(k)}$ = average of all the initial momentums ($Mom^{(k)}_i$). If $\left\|ResMom^{(k)}\right\|$ was below the threshold, then stop.

(3) Applying the *EPDiff* equation [5] to $ResMom^{(k)}$ and integrating the resulted velocity fields, we would obtain the residual deformation $ResDef^{(k)}$.

(4) The transformed DSI dataset was $TDSI^{(k)}_i = DSI_i \circ Def^{(k)}_i \circ ResDef^{(k)}$.

(5) Finally, $DSI^{(k+1)}_{template}$ = average of all the transformed DSI datasets ($TDSI^{(k)}_i$).

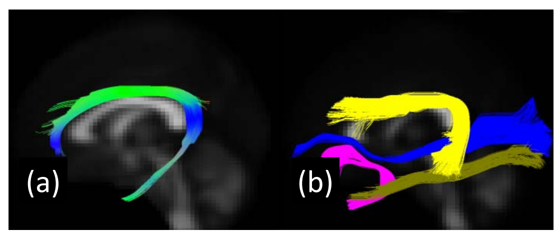

Figure 2

In the study, N=70, K=3, and the above estimation procedure was implemented in a multi-resolution manner.

Results: Figure 1 shows the results of selected slices of the b0 images (top row), the GFA maps (middle row) and the ODF maps (bottom row) of the estimated DSI template. Though it is the average of seventy DSI datasets, the results could reveal the important white matter structures. Since it is the mean image, it is expected to be apparently symmetry; the results visually match the expectation. Figure 2 shows the tractography of (a) the left cingulum bundle, (b) the left arcuate fasciculus (yellow) and the left inferior fronto-occipital fasciculus (blue), the left uncinate fasciculus (pink), the left inferior longitudinal fasciculus (brown); all the tracts are consistent with the anatomical descriptions in the literature. Figure 3 plots the absolute values of the residual momentums, which shows that it converges in 3 iterations.

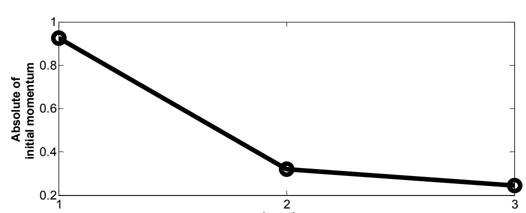

Figure 3

Discussion: The present study demonstrates a method which could effectively estimate the group-specific DSI template. In principle, the estimation method is embedded in the LDDMM framework, which offers the method several good properties. First, the template is defined as the one where the sum of the initial momentums from the template to each of the DSI dataset in the group vanishes. This definition corresponds to an interesting property: at convergence, the sum of squared distances between the template and the DSI datasets is minimum. Second, the transformation between the DSI template and each DSI dataset in the group is diffeomorphic. Third, the initial momentum from the DSI template to each DSI dataset encodes the whole transformation; therefore it's possible to investigate the shape differences in the template space via the initial momentums. Note the present method transforms the whole DSI dataset to the template space; hence we can analyze not only the differences in the image space but the variability in the q-space.

References: [1]Ma, J., et al., Neuroimage, 2008. 42(1): p. 252-61. [2]Ashburner, J., Neuroimage, 2007. 38(1): p. 95-113. [3]Wedeen, V.J., et al., Magn Reson Med, 2005. 54(6): p. 1377-86. [4]Hsu, Y.C., C.H. Hsu, and W.Y.I. Tseng, Proc. ISMRM., 2010. [5] Miller, A., A. Trouve, and L. Younes, Journal of Mathematical Imaging and Vision, 2006. 24: p. 209-228.