Multi-contrast Large Deformation Diffeomorphic Metric Mapping and Diffusion Tensor Image Registration

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Introduction

Large Deformation Diffeomorphic Metric Mapping (LDDMM) is a nonlinear registration algorithm which calculates diffeomorphic transformations between scalar images [1]. The diffeomorphisms are invertible and smooth maps with a smooth inverse. In this work, we extend this algorithm to multi-contrast LDDMM (mc-LDDMM) for inter-subject registration of diffusion tensor images (DTI) [2]. Different scalar valued isotropy and anisotropy images obtained from DTI data were used to drive the registration with their different contrast information.

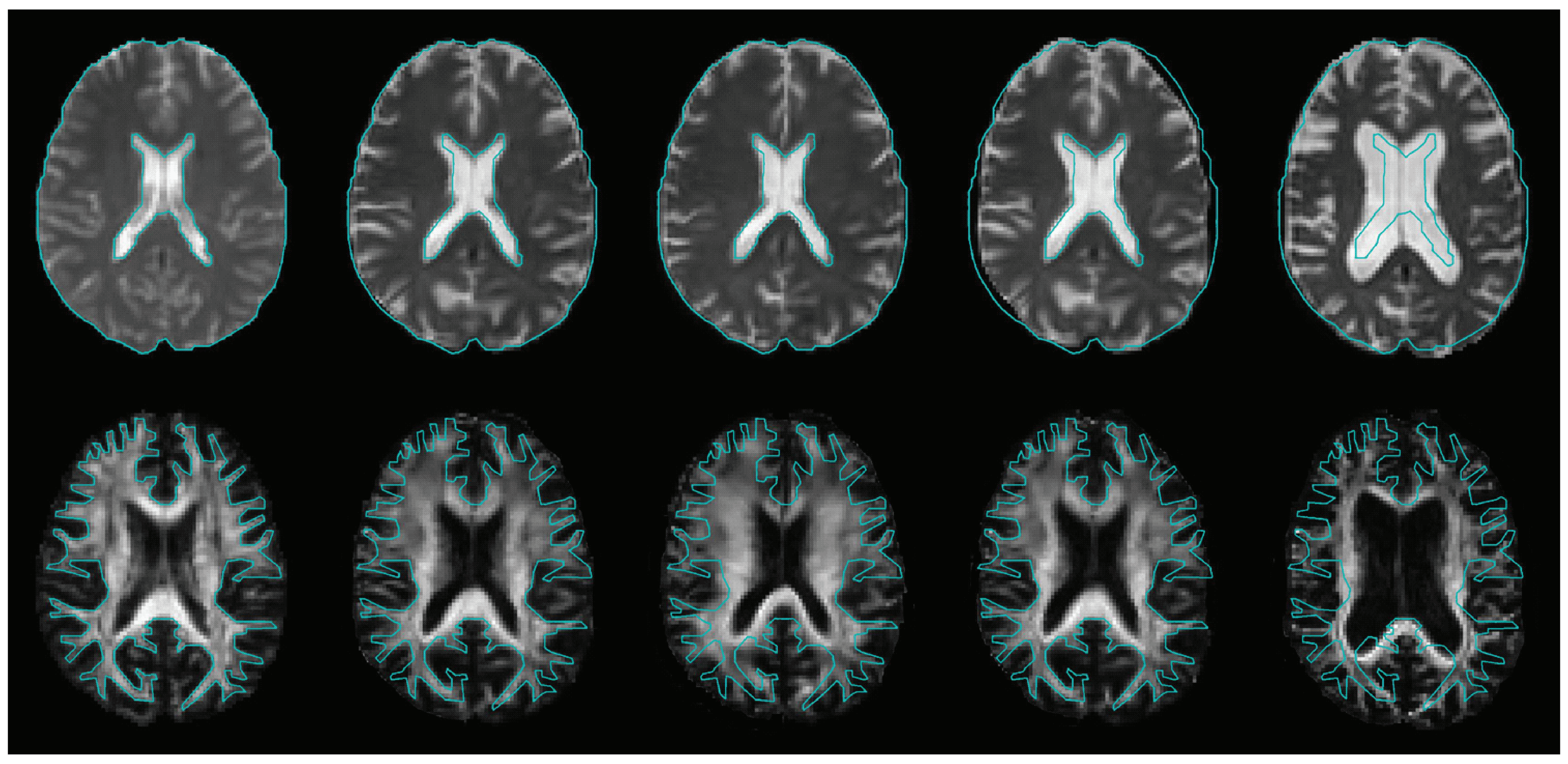
Methods

DTI data from 18 normal adult subjects were used in this study. Each subject had a 6 parameter tensor field image and a minimal diffusion weighted (b ≈ 33mm2/sec) b0 image. Additionally, fractional anisotropy (FA) images were calculated from the tensor fields.

Initially, each subject was registered to a single-subject atlas using affine transformations calculated with the b0 images. The subjects were further registered to the atlas using mc-LDDMM. To do this each subject and atlas data were modeled as a vector valued image. For any given two vector valued images, $I_0 = [I_{01}, I_{02}, ..., I_{0C}]$ and $I_1 = [I_{11}, I_{12}, ..., I_{1C}]$ with $I_{0c}, I_{1c} : \Omega \subset R^3 \rightarrow R, c = 1, ..., C$ mc-LDDMM calculates the diffeomorphic transformation, φ, registering these two images, such that $I_1 = I_0 \circ \varphi^{-1}$ or $[I_{11}, I_{12}, ..., I_{1C}] = [I_{01} \circ \varphi^{-1}, I_{02} \circ \varphi^{-1}, ..., I_{0C} \circ \varphi^{-1}]$. φ is assumed to be generated as the end point of the flow of the smooth time-dependent vector field, $v_t \in V$, with the ordinary differential equation, $\partial\phi_t^v / \partial t = v_t(\phi_t^v), t \in [0,1]$. The optimal transformation, $\hat{\varphi}$ is calculated by integrating the vector field, which is found by minimizing the following equation with the gradient descent algorithm.

$$\hat{v} = \underset{v : d\phi_t^v / dt = v_t(\phi_t^v)}{\arg\min} \left(\int_0^1 \|v_t\|_V^2 \, dt + \sum_{c=1}^{C} \left\{ \frac{1}{\sigma_c^2} \left\| I_{0c} \circ \varphi^{-1} - I_{1c} \right\|_{L^2}^2 \right\} \right)$$

To register subjects to the atlas, different choices of contrast images were used to drive the registration. These were: b0 image only; FA image only; and b0+FA dual-contrast registration. Figure-1 shows an example registration with the atlas image boundaries overlaid on original and transformed subject images. In all transformations, we used the tensor reorientation strategy in [3].



Atlas | Subject after b0-FA LDDMM | Subject after b0 LDDMM | Subject after FA LDDMM | Subject

Figure-1

To compare the accuracy of these different registrations, anatomical features were manually defined on the template and subject images. These features are 237 landmarks defined on the white matter structures of FA images (Figure-2 left), the outer brain surface and ventricle surfaces defined on b0 images (Figure-2 middle and right). These features on the subjects were then moved onto the atlas using the calculated transformations. Then the errors between atlas and subject features were calculated for different type of registrations.

References:

[1] Beg, M.F., M.I. Miller, A. Trouve, and L. Younes. "Computing Large Deformation Metric Mapping via Geodesic Flows of Diffeomorphisms". IJCV 61. 2 (2005):139-157.

[2] Ceritoglu C. "Multichannel large deformation diffeomorphic metric mapping and registration of diffusion tensor images". PhD thesis, The Johns Hopkins University (2008).

[3]Alexander, D.C., Pierpaoli, C., Basser, P.J., Gee, J.C. "Spatial transformations of diffusion tensor magnetic resonance images. IEEE Transactions on Medical Imaging". (2001) vol. 20, no. 11, pp. 1131-1139.

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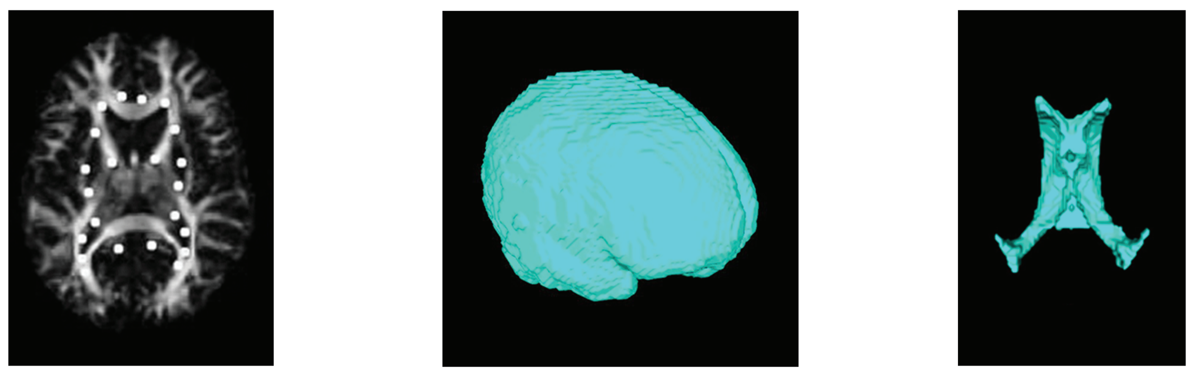
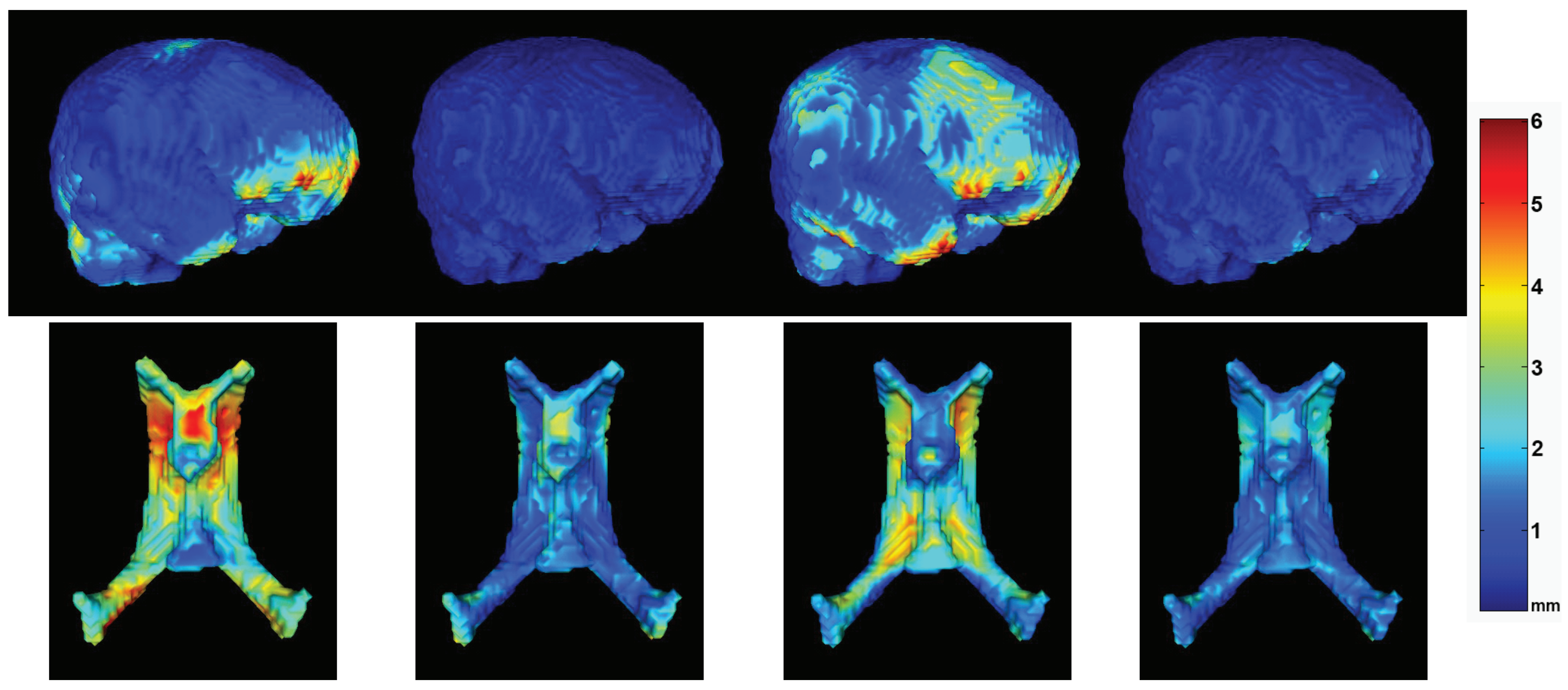


Landmarks | Brain surface | Ventricle surface

Figure-2

Results

Figure-3 shows the avreage of the errors between subject and atlas surfaces before and after registration with mc-LDDMM using different contrast images.



Before LDDMM | b0 LDDMM | FA LDDMM | b0-FA LDDMM

Figure-3

Figure-4 shows the cumulative distribution of the average of the errors between subject and atlas landmarks and surface vertices for different registration types.

The registration accuracy measured by average landmark distance was 3.51±1.16 before LDDMM transformation, 1.65±0.47 after FA-LDDMM, 3.12±0.54 after b0-LDDMM and 1.88±0.55 b0+FA-LDDMM. Statistically significant improvement in the registration accuracy was observed by using FA (p=0.001) or b0+FA (p =0.01) mappings at 5% significance level.

The FA- LDDMM led to poor normalization quality for the brain surface matching. The b0 image with high contrast for the brain boundary led to significant improvement in normalization. The same results were observed for the ventricle shape matching. Although significant improvement was found by the FA-LDDMM, the b0 contrast is necessary for better registration accuracy. (Figure-4)

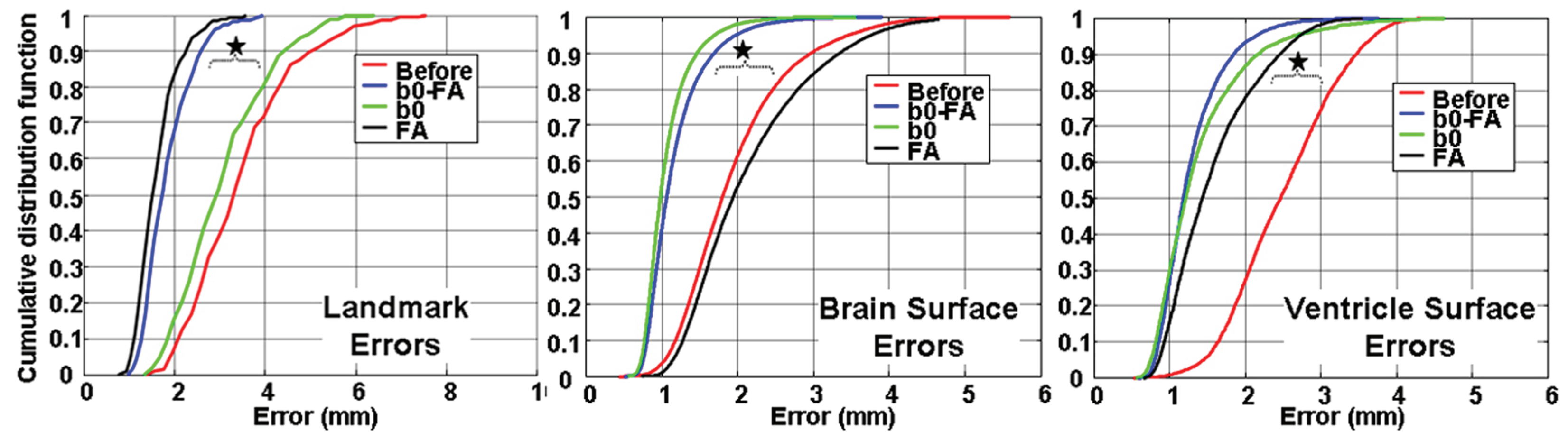


Figure-4

Conclusion

We evaluated an LDDMM-based normalization method by testing single and two-contrast approaches using b0 and FA contrasts. Based on registration accuracy of manually defined image feature measurements as gold standard, we found that the two-contrast approaches(FA+b0) can register the entire brain with higher spatial accuracy. In our work, we used different contrast information from scalar maps of DTI data for DTI registration with multi-contrast LDDMM. Other types of image modalities or information can also be used in mc-LDDMM for inter-subject image registration.

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