

A New Algorithm to Estimate the Mean of A Group of Tract Bundles

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Introduction: In neuroimaging studies, it is usually necessary to register a group of anatomical images to a common space (usually defined by a template) for group comparisons. Rather than employing a standard space (e.g., the MNI template) as the common space, an emerging trend is to register all of the images under study to a “mean” image which is constructed by all of the individual images themselves. The mean image (group template) is usually believed to better represent the anatomical features of the study population than the exterior one, thus using the mean image as the registration target would lead to higher statistical power. Many methods have been proposed to construct the group template from a population of images, and most of the methods focus on density images, such as T1w images [1] and diffusion spectrum images (DSI) [2]. Apart from density images, brain anatomy could be investigated using tract bundles which are reconstructed from diffusion MR images. Constructing the mean of a group of specific tract bundles would facilitate computational anatomy. However, to the best of our knowledge, few studies address this issue. In the present study, we proposed an algorithm to iteratively estimate the mean of a group of tract bundles.

Algorithm: A natural way to construct the mean tract bundle is to impose the tract bundles in a metric space and estimate the Karcher mean (the one with minimal sum of distances) of the tract bundles using the registration method, LDDMM-unlabeled curves [3]. We can choose one tract bundle as the initial estimate and iteratively search the solution; however, this approach would encounter a bias problem: different starting points may produce different results. Hence, we proposed to estimate the Karcher mean by considering the tract bundles altogether. One of the difficulties of this approach is that the “addition” and “average” operations, unlike density images, are not properly defined for tract bundles. For diffusion MR images such as DTI, QBI or DSI, we usually reduce the data to an orientation map (v), and then perform fiber-tracking techniques on the map to produce tract bundles (T), that is, $T = Fv$, where F represents the operation of fiber-tracking. The inverse of the operation, $v = F^{-1}T$, can be achieved via modeling the tract bundles as currents [4]. Explicitly, F^{-1} is defined through a smoothing kernel K^W such that $v(x) = \sum_{t_i \in T} \int_{y \in t_i} K^W(x, y) \tau_i(y) dy$, where τ_i is the tangent vector of curve t_i . Different from T space, the “addition” and “average” operations are well-defined in the v space. As a result, the fundamental strategy of our algorithm is: performing registration in the T space and taking the average in the v space. Given a set of tract bundles $T_j, j = 1 \dots N$. The deformation maps of T_j for iteration k are ϕ_j^k . Let $\phi_j^0 = Id$, for iteration $k = 1 \dots K$, our algorithm is performed as the following steps:

- (1) Converting tract bundles to orientation maps, $v_j^k = F^{-1}(\phi_j^{k-1} T_j)$.
- (2) Taking the average of the orientation maps, $\bar{v}^k = \frac{1}{N} \sum_{j=1}^N v_j^k$.
- (3) Converting the mean orientation map to mean tract bundle, $\bar{T}^k = F\bar{v}^k$.
- (4) Registering \bar{T}^k to $T_j, j = 1 \dots N$ using the LDDMM-unlabeled curves [3] algorithm, resulting in deformation maps $\phi_j^k, j = 1 \dots N$.
- (5) If it reaches the maximum number of iterations or if the energy reduction is lower than a predefined threshold, then stop. Otherwise, go to the next iteration.

Materials and methods for demonstration: Ten subjects were randomly selected from the IXI database [5], and right cingulum bundles were extracted from their DTI datasets by fiber-tracking. After normalizing the T1w images to the MNI space, the rotation matrices were estimated from the deformation maps and were applied to the corresponding cingulum bundles so that they were rigidly aligned, as shown in Fig. 1. Our proposed

algorithm was then applied to these aligned cingulum bundles to estimate their mean. For the F^{-1} operator, K^W was a Gaussian with $\sigma = 9$ mm. For the LDDMM-unlabeled curves algorithm, the transformation flow was divided into 10 steps and the kernels of space V and W were all Gaussian with $\sigma_V = 30$ mm and $\sigma_W = 9$ mm, respectively. In the study, $K = 4$.

Results: Fig. 2 shows the results during the estimation process. The left column of Fig. 2 is the orientation maps, where the vector orientations are indicated by the unit-length whiskers and the vector lengths are represented by the background image. The right column of Fig. 2 is the tracking results of the left column. We can see that the maps of vector length become sharper as the iterations proceed, especially in the head and tail regions. Similar results are observed in the mean cingulum bundle. In the head and tail regions, the bundles become denser in latter iterations. The shape of the cingulum bundle of the final iteration looks properly representing the shape of the native tract bundles shown in Fig. 1.

Discussion: The present study proposed an approach to estimate the mean shape of a group of tract bundles. This method was demonstrated in ten right cingulum bundles and the results show that our algorithm could effectively produce a mean of the cingulum bundles. Our approach considers all of the tract bundles altogether during estimation and avoids the bias problem which one usually encounters if one of the tract bundles is selected as the initial estimate. However, the algorithm has at least two limitations. First, many factors affect the final results, including the smoothing kernel K^W in operator F^{-1} , the employment of fiber-tracking algorithm (i.e., the F operator), parameters in the LDDMM-unlabeled curves algorithm, etc. So it requires preliminary testes to decide the optimal parameters and will be extensively investigated in future study. Second, the orientation map is limited to a map of single vectors; the method cannot deal with the crossing-fiber situation. In conclusion, the proposed algorithm can estimate the mean shape of a group of tract bundles, and has the potential to facilitate computational anatomy of the brain.

[1] J. Ashburner, Neuroimage, pp. 95-113, Oct 15 2007. [2] Y. C. Hsu et al., ISMRM 2012. [3] Y. C. Hsu and W. Y. I. Tseng, ISMRM 2013. [4] S. Durrleman et al., Neuroimage, pp. 1073-90, 2011. [5] IXI Database. Available: <http://biomedic.doc.ic.ac.uk/brain-development/>

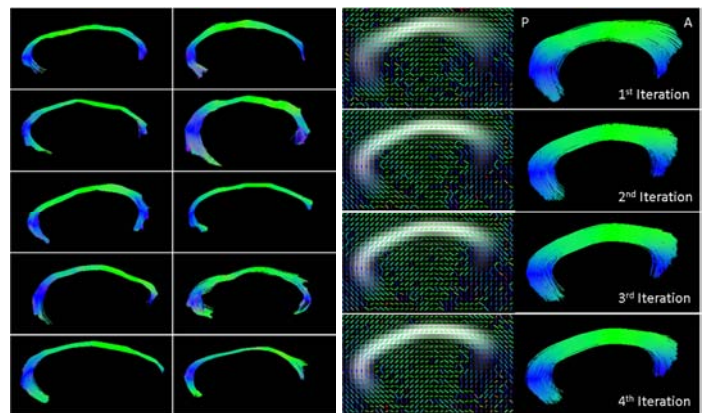


Fig. 1

Fig. 2