

# Large Deformation Diffeomorphic Metric Mapping for Unlabeled Curves: Application to Fiber Tract Bundles

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**Introduction:** Registration of brain anatomies is one of most important techniques for neuroimaging studies and it has been richly studied in the last decades. In terms of the anatomical objects the registration methods addressing on, the registration methods can be roughly divided into several categories: points, curves, surfaces and volume (dense) images. The registration method employed by the voxel-based morphometry (VBM) method [1] belongs to the forth category, in which a set of volume images are usually registered to a common template space. VBM is a popular and successful analysis method and has been shown to have the potential to detect group differences in gray/white matter concentrations. Another popular analysis method, known as surface-based morphometry (SBM), is to register a set of cortical surfaces and then perform the morphometry analyses. Besides volume images and cortical surfaces, in the neuroimaging field, an emerging anatomical object is getting more and more attentions, the fiber tract bundles reconstructed by tractography. Because of the successes of VBM and SBM, it would be interesting and valuable to investigate the brain morphology in terms of reconstructed tract bundles. However, currently it lacks an appropriate method designed for registering tract bundles, and the present study is to fill the vacancy.

**Materials and methods:** The proposed method is a generalized version of the LDDMM-curve method [2], of which the mathematical formulations and the numerical implementation details have been comprehensively discussed in [2]. Briefly, given two curves  $c$  and  $s$ , the goal is to find a deformation field  $\varphi_1$  such that  $\varphi_1 \cdot c = s$ . LDDMM-curve models the registration as fluid flow, in which  $\varphi_1$  is constructed by integrating the ODE:  $\dot{\varphi}_t = v_t \circ \varphi_t$  with the initial condition  $\varphi_0 = Id$ , where  $v: v_t \in V, t \in [0,1]$  are time-varying vector fields belonging to a smoothing Hilbert space  $V$ . Under this setting, instead of estimating  $\varphi_1$  directly, LDDMM-curve attempts to find the optimal  $v$  which minimizes the energy  $E(v) = E_1(v) + E_2(v) = \frac{1}{2} \int_0^1 \|v_t\|_V^2 dt + \frac{1}{2\sigma^2} \|\mu_{\varphi_1^v(c)} - \mu_s\|_{W^*}^2$ , where  $\|v\|_V$  is the norm of  $v$  in the space  $V$  and  $\|\mu_c\|_{W^*}$  is the dual norm of vector-valued measure  $\mu_c$ .  $E_1$  is a regularization term to ensure the smoothness of the estimated deformation fields and  $E_2$  is a data-matching term which evaluates the mismatching between  $\varphi_1^v \cdot c$  and  $s$ . In the situation of registering multiple curve pairs  $c_i$  and  $s_i, i = 1 \dots N$ , LDDMM-curve can be extended by making  $E_2 = \frac{1}{2\sigma^2} \sum_{i=1}^N \|\mu_{\varphi_1^v(c_i)} - \mu_{s_i}\|_{W^*}^2$  so that in convergence the pairs of curves are registered altogether. In practice, the labeling (i.e., pairing) of the curves usually requires prior knowledge which makes it encounters some problems when employing the conventional LDDMM-curve method to register two tract bundles. First, in most cases, the tract bundles have different numbers of curves, which in turn makes it impossible to label the curve pairs. Second, even if the numbers of curves are the same, it is impractical to label the curves due to the fact that each tract bundle usually contains more than hundreds of curves. To address these problems, in the present study, we treated the curves in a tract bundle unlabeled and generalized the conventional LDDMM-curve method to register the unlabeled curves. More specifically, given two tract bundles  $T_0 = \{c_i, i = 1 \dots M\}$  and  $T_1 = \{s_j, j = 1 \dots N\}$ , we reformulated the data-matching functional with  $E_2 = \frac{1}{2\sigma^2} \|\sum_{i=1}^M \mu_{\varphi_1^v(c_i)} - \sum_{j=1}^N \mu_{s_j}\|_{W^*}^2$ . This formulation can be understood as that all of the curves in a tract bundle were concatenated into a single curve. For demonstration, two right cingulum bundles were employed in the study, in which  $T_0$  contains 156 curves and  $T_1$  124 curves. We implemented the optimization algorithm which has been detailed in [2], excepting that the data-matching term was modified in order to register unlabeled curves as discussed above. The kernels of space  $V$  and  $W$  were all Gaussian with  $\sigma_V = 30$  mm and  $\sigma_W = 9$  mm. The transformation flow was divided into 10 steps.

**Results:** Fig. 1 shows the right cingulum bundles  $T_0$  (a) and  $T_1$  (b) and the registration results. We can see that the overall shape of the transformed  $T_0$  (c) matches  $T_1$  well and the global form the transformed  $T_1$  (d) also effectively matches  $T_0$ .

**Discussion:** The present study proposed an approach to register the unlabeled curves. We apply the proposed method to register two right cingulum bundles, and the results show that the global shapes are effectively registered, suggesting that it has the potential to investigate the brain morphology in terms of tract bundles, which would be a valuable tool for neuroimaging studies in development, ageing or mental disorders. The proposed method is an extension of the LDDMM-curve method by treating all of the curves in a tract bundle connected with the “head-to-tail” scheme. Under the LDDMM framework, the initial momentum encodes the entire geodesic flow, indicating that the brain anatomy (tract bundle here), which is in the curved shape space, can be analyzed on a linear space.

**References:** [1] J. Ashburner and K. J. Friston, Neuroimage, vol. 11, pp. 805-21. [2] J. Glaunes, A. Qiu, M. I. Miller, and L. Younes, Int J Comput Vis, vol. 80, pp. 317-336.

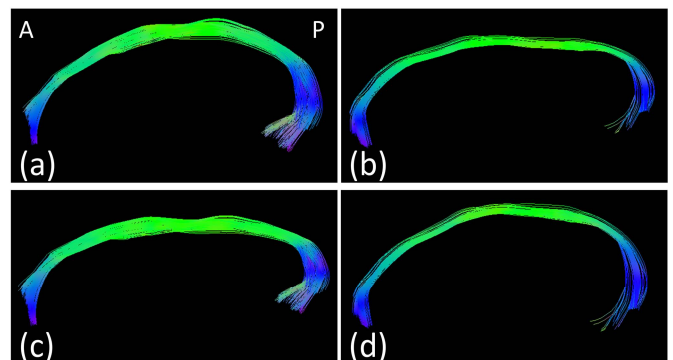


Fig. 1