Fiber-Driven Resolution Enhancement of Diffusion-Weighted Images - An Evaluation Using High Resolution Data

Pew-Thian Yap[1], Hongyu An[1], Yasheng Chen[1], and Dinggang Shen[1]
[1]*Department of Radiology and BRIC, University of North Carolina, Chapel Hill, North Carolina, United States*

Introduction: Diffusion-weighted imaging (DWI), while giving rich information about brain circuitry, often suffers from low spatial resolution. This abstract describes a fiber-driven algorithm for enhancing the resolution of DWI data. The fundamental premise is that, to best preserve information, interpolation should always be performed with data along fiber streamlines. To achieve this, at each spatial location, we probe neighboring voxels in various directions to gather diffusion information for data reconstruction. Based on the fiber orientation distribution function (ODF), directions that are more likely to be traversed by fibers will be given greater weights during interpolation. This ensures that the data used for interpolation is only contributed by diffusion data coming from fibers that are aligned with a specific direction. This approach respects local fiber structures and prevents blurring resulting from averaging of data from significantly misaligned fibers.

Methods: To increase resolution, the image domain is divided using a grid with grid elements that are smaller than the acquired voxel size. The DWI data for each of these grid elements are then reconstructed using the following steps:

1) Local Fiber Profiling. To determine the probability of whether voxel location $\boldsymbol{x}$ is traversed by fibers in direction $\boldsymbol{v}_k$ $(k = 1, \dots, M)$, we profile the field of fiber ODFs $\{p(\boldsymbol{x}_i, \boldsymbol{v}) | \boldsymbol{x}_i \in N(\boldsymbol{x})\}$ along direction $\boldsymbol{v}_k$. $N(x)$ is a neighborhood of voxels in the vicinity of $\boldsymbol{x}$. The local fiber configuration at $\boldsymbol{x}$ is characterized by a *fiber orientation profile*, which is a directional function that allows for anisotropic collection of neighboring information to reconstruct the DWI data at location $\boldsymbol{x}$. It is determined as:

$$\hat{p}(\boldsymbol{x}, \boldsymbol{v}_k) = \frac{\sum_{\boldsymbol{x}_i \in N(x)} w(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k) p(\boldsymbol{x}_i, \boldsymbol{v}_k)}{\sum_{\boldsymbol{x}_i \in N(x)} w(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k)} = \sum_{\boldsymbol{x}_i \in N(x)} \tilde{w}(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k) p(\boldsymbol{x}_i, \boldsymbol{v}_k)$$

where $\tilde{w}(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k) = w(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k) / \sum_{\boldsymbol{x}_i \in N(x)} w(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k)$. We define the weights as $w(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k) = \exp(-0.5 d_{\text{axial}}^2(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k) / \sigma_{\text{axial}}^2) \exp(-0.5 d_{\text{radial}}^2(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k) / \sigma_{\text{radial}}^2)$. Here d_{axial} and d_{radial} are respectively the axial distance (parallel length) and the radial distance (perpendicular length) to a reference line defined by $\boldsymbol{x}$ and $\boldsymbol{v}_k$. Parameters σ_{axial} and σ_{radial} control the falloff of the weight with respect to the axial and radial distances, respectively.

2) Fiber-Sensitive Interpolation With Rician-Bias Correction. The fiber orientation profile at location $\boldsymbol{x}$ gives an indication of which directions are most likely to be traversed by fibers. The DWI data of voxels in the neighborhood of $\boldsymbol{x}$ should therefore be weighted according to the fiber orientation profile, i.e., directions that are more likely to be traversed by fibers should be given greater weights. To reconstruct the DWI data at location $\boldsymbol{x}$, we compute

$$S(\boldsymbol{x}, \boldsymbol{g}_l) = [\bar{S}^2(\boldsymbol{x}, \boldsymbol{g}_l) - 2\sigma_{\text{rician}}^2]_+^{1/2}, \quad \bar{S}^2(\boldsymbol{x}, \boldsymbol{g}_l) = \frac{\sum_{\boldsymbol{x}_i \in N(x)} \rho(\boldsymbol{x}_i, \boldsymbol{x}) S^2(\boldsymbol{x}_i, \boldsymbol{g}_l)}{\sum_{\boldsymbol{x}_i \in N(x)} \rho(\boldsymbol{x}_i, \boldsymbol{x})}, \quad l = 1, \dots, N$$

where $\rho(\boldsymbol{x}_i, \boldsymbol{x}) = \sum_k \tilde{w}(\boldsymbol{x}_i, \boldsymbol{x}, \boldsymbol{v}_k) \hat{p}(\boldsymbol{x}, \boldsymbol{v}_k)$ and $[z]_+ = z$, if $z > 0$; 0 otherwise. Note that the squared signal values are used here so that the statistical bias $2\sigma_{\text{rician}}^2$ can be removed for unbiased estimation. The noise variance σ_{rician}^2 can be estimated from the background signal using $\sigma_{\text{rician}}^2 = \langle S_{\text{background}}^2 \rangle / 2$.

Results: To evaluate the proposed algorithm, we a acquired a set of high resolution (1mm)^3 diffusion weighted images using the technique described in [1]. We down-sampled the acquired data by averaging every eight voxels. The proposed algorithm was then applied to this down-sampled data to generate the resolution-enhanced data with resolution (1mm)^3. The results, shown in Fig. 1, indicate that our method is able to generate realistic resolution-enhanced data that greatly resembles the data scanned at high resolution. This implies that, in situation where the luxury of scanning in high resolution is not attainable, our algorithm can be used as an effective means for post-processing enhancement.

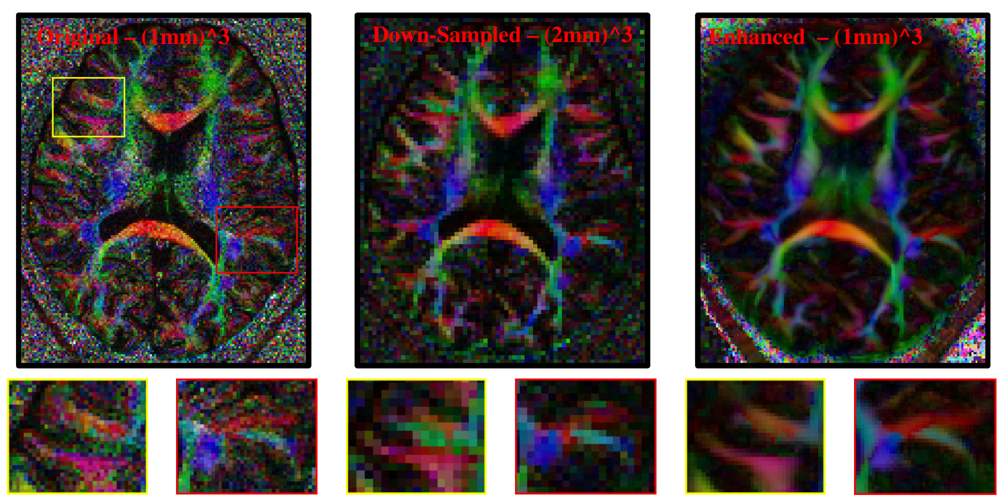

Fig. 1. Color-coded fractional anisotropy images of the original data, down-sampled data, and resolution-enhanced data.

Conclusion: We have presented an algorithm for the resolution enhancement of diffusion-weighted images by leveraging the assumption that fibers are locally linear continuous.

References: [1] Porter and Heidemann, Magnetic Resonance in Medicine, vol. 62, pp. 468–475, 2009.