Published in final edited form as:

Comput Diffus MRI (2016). 2016 October ; 2016: 113–121.

Robust Construction of Diffusion MRI Atlases with Correction for Inter-Subject Fiber Dispersion

Zhanlong Yang^{1,3}, Geng Chen^{2,3}, Dinggang Shen³, and Pew-Thian Yap³

¹College of Marine, Northwestern Polytechnical University, Xi'an, China

²Data Processing Center, Northwestern Polytechnical University, Xi'an, China

³Department of Radiology and BRIC, UNC Chapel Hill, U.S.A

Abstract

Construction of brain atlases is generally carried out using a two-step procedure involving registering a population of images to a common space and then fusing the aligned images to form an atlas. In practice, image registration is not perfect and simple averaging of the images will blur structures and cause artifacts. In diffusion MRI, this is further complicated by the possibility of within-voxel fiber misalignment due to natural inter-subject orientation dispersion. In this paper, we propose a method to improve the construction of diffusion atlases in light of inter-subject fiber dispersion. Our method involves a novel q -space (i.e., wavevector space) patch matching mechanism that is incorporated in a mean shift algorithm to seek the most probable signal at each point in q -space. Our method relies on the fact that the mean shift algorithm is a *mode seeking* algorithm that converges to the mode of a distribution and is hence robustness to outliers. Our method is therefore in effect seeking the most probable signal profile at each voxel given a distribution of profiles. Experimental results confirm that our method yields cleaner fiber orientation distribution functions with less artifacts caused by dispersion.

Keywords

Diffusion MRI; Atlases; x - q Space; Azimuthal Equidistant Projection; Patch Matching; Mean Shift

1 Introduction

Brain atlases [1,2] capture the common features of image populations and play crucial roles in the processing and analysis of brain images. They are widely used for guiding brain tissue segmentation, normalization of images to a common space, and brain labeling with regions of interest. Unlike atlases of T_1 -weighted images, diffusion MRI atlases afford additional white matter microstructural information that can be harnessed for tissue characterization and axonal tracing. To ensure that the microstructural information captured at each voxel location is properly encoded in the atlas, dedicated techniques are needed.

Correspondence to: Pew-Thian Yap.

Z. Yang and G. Chen contributed equally to this work.

Atlas construction generally involves fusing a population of images that are registered to a common space. However, in practice, perfect registration is difficult, if not impossible. Averaging misaligned images to construct an atlas blurs structures and introduces artifacts. In diffusion MRI [3], the problem is even more challenging, since the alignment of gross anatomical structures does not necessarily guarantee the alignment of the microstructural information captured in each voxel. In this situation, it is unclear for example how signals characterizing fiber bundles of varying orientations, which can occur naturally across subjects, should be fused to form the atlas. Moreover, the commonly used simple averaging method is sensitive to outliers. For instance, if the distribution of signal profiles of single-directional fiber bundles is contaminated with a small number of signal profiles of crossing fibers, simple averaging will result in a crossing profile, albeit with a small secondary peak. This outcome apparently is not representative of the majority.

In this paper, we propose a novel q -space patch-matching mechanism that is incorporated in a mean shift algorithm to seek the most probable signal at each point in q -space. Mean shift is a versatile non-parametric iterative algorithm that can be used for mode seeking [4]. Instead of the mean, our method employs the mean shift algorithm to determine the mode of a distribution of signal profiles. The mean shift algorithm uses a kernel to measure the distance between signals. To increase robustness to noise, we measure the distance between signals using patches defined in the q -space. Patch matching is key to the success of many state-of-the-art denoising algorithms, such as non-local means [5]. We perform patch matching in q -space with the help of azimuthal equidistant projection [6] and rotation invariant features [7]. Experimental results confirm that our method yields diffusion atlases with cleaner fiber orientation distribution functions and less artifacts caused by inter-subject fiber dispersion.

2 Approach

Our method employs neighborhood matching in q -space for effective atlas construction. For each point in the x - q space, $(\mathbf{x}_i, \mathbf{q}_k)$, where $\mathbf{x}_i \in \mathbb{R}^3$ is a voxel location and $\mathbf{q}_k \in \mathbb{R}^3$ is a wavevector, we define a spherical patch, $\mathcal{P}_{i,k}$, centered at $\mathbf{q}_k$ with fixed $q_k = |\mathbf{q}_k|$ and subject to a neighborhood angle α_p . The diffusion measurements on this spherical patch are mapped to a disc using azimuthal equidistant projection (AEP) before computing the rotation invariant features via polar complex exponential transform (PCET) (Section 2.1) [7] for patch matching (Section 2.2). The similarity weights resulting from patch matching will be used in the mean shift algorithm (Section 2.3) to determine the most probable signal at each point in q -space.

2.1 Patch Features

Azimuthal equidistant projection (AEP) [6] maps the coordinates on a sphere to a plane where the distances and azimuths of points on the sphere are preserved with respect to a reference point [6]. This provides a good basis for subsequent computation of invariant features for matching. The reference point (ϕ_0, λ_0) , with ϕ being the latitude and λ being the longitude, corresponds in our case to the center of the spherical patch and will be projected to the center of a disc. Viewing the reference point as the ‘North pole’, all points along a

given azimuth, θ , will project along a straight line from the center of the disc. In the projection plane, this line subtends an angle θ with the vertical. The distance from the center to another projected point is given as ρ . The projection can be described as $\mathbf{q} \rightarrow (q, \rho, \theta)$. Based on [6], distance ρ associated with a point (ϕ, λ) on the sphere is computed as the great circle distance between the point and the reference (ϕ_0, λ_0) and is given by

$$\cos \rho = \sin \phi_0 \sin \phi + \cos \phi_0 \cos \phi \cos(\lambda - \lambda_0). \quad (1)$$

The angle θ is computed as the azimuth of the point in relation to the reference:

$$\tan \theta = \frac{\cos \phi \sin(\lambda - \lambda_0)}{\cos \phi_0 \sin \phi - \sin \phi_0 \cos \phi \cos(\lambda - \lambda_0)}. \quad (2)$$

Note that, since the diffusion signals are antipodal symmetric, we map antipodally all the points on the sphere to the same hemisphere as the reference point prior to performing AEP. After projection, the q -space spherical patch $\mathcal{P}$ is mapped to a 2D circular patch $\hat{\mathcal{P}}$.

After AEP, we proceed with the computation of rotation invariant features. We choose to use the polar complex exponential transform (PCET) [7] for its computation efficiency. PCET with order n , $|n| = 0, 1, 2, \dots, \infty$, and repetition l , $|l| = 0, 1, 2, \dots, \infty$, of AEP-projected signal profile $S(\mathbf{x}, q, \rho, \theta)$ is defined as

$$M_{n,l}(\hat{\mathcal{P}}) = \frac{1}{\pi} \int_{(\mathbf{x}, q, \rho, \theta) \in \hat{\mathcal{P}}} [H_{n,l}(\rho, \theta)]^* S(\mathbf{x}, q, \rho, \theta) \rho \, d\rho \, d\theta, \quad (3)$$

where $[\cdot]^*$ denotes the complex conjugate and $H_{n,l}(\rho, \theta)$ is the basis function defined as

$$H_{n,l}(\rho, \theta) = e^{i2\pi n \rho^2} e^{il\theta}. \quad (4)$$

For each patch $\hat{\mathcal{P}}$ consisting of signal vector $\mathbf{S}(\hat{\mathcal{P}})$, the associated PCET features $\{|M_{n,l}(\hat{\mathcal{P}})|\}$ computed up to maximum order m (i.e., $0 \leq |n| \leq m$) are concatenated into a feature vector $\mathbf{M}(\hat{\mathcal{P}})$.

2.2 Patch Matching

The similarity of a reference patch $\hat{\mathcal{P}}_{i,k}$ with another patch $\hat{\mathcal{P}}_{j,d}$ associated with the d -th subject is characterized by weight

$$w_{i,k;j,l}(d) = \frac{1}{Z_{i,k}} \exp \left\{ -\frac{\|\mathbf{M}(\hat{\mathcal{P}}_{i,k}) - \mathbf{M}(\hat{\mathcal{P}}_{j,l}(d))\|_2^2}{h_M^2(i,k)} \right\} \exp \left\{ -\frac{\|\mathbf{x}_i - \mathbf{x}_j\|_2^2}{h_x^2} \right\}, \quad (5)$$

where $Z_{i,k}$ is a normalization constant to ensure that the weights sum to one. Here $h_M(i,k)$ is a parameter that controls the attenuation of the exponential function. As in [8], we set

$h_M(i,k) = \sqrt{2\beta\hat{\sigma}_{i,k}^2|\mathbf{M}(\hat{\mathcal{P}}_{i,k})|}$, where β is a constant [8] and $\hat{\sigma}_{i,k}^2$ is the estimated noise standard deviation, which can be computed globally as shown in [9] or spatial-adaptively as shown in [8]. The former is used in this paper. Parameter $h_x = \sqrt{2}\sigma_x$ controls the attenuation of the second exponential function, where σ_x is a scale parameter. $|\mathbf{M}(\hat{\mathcal{P}}_{i,k})|$ denotes the length of the vector $\mathbf{M}(\hat{\mathcal{P}}_{i,k})$.

Given D subjects, a “mean” signal can be computed based on the weights resulting from patch matching:

$$\bar{S}(\mathbf{x}_i, \mathbf{q}_k) = \sqrt{\sum_{d=1}^D \sum_{(\mathbf{x}_j, \mathbf{q}_l) \in \mathcal{V}_{i,k}} w_{i,k;j,l}(d) S^2(\mathbf{x}_j, \mathbf{q}_l; d) - 2\sigma^2}, \quad (6)$$

where $S(\mathbf{x}_j, \mathbf{q}_l; d)$ is the measured signal associated with the d -th subject at location $\mathbf{x}_j \in \mathbb{R}^3$ with wavevector $\mathbf{q}_l \in \mathbb{R}^3$. $\mathcal{V}_{i,k}$ is a local x - q space neighborhood associated with $(\mathbf{x}_i, \mathbf{q}_k)$, defined by a radius r_s in x -space and an angle α_s in q -space. Note the bias associated with the Rician noise distribution is removed in this process [9]. σ is the Gaussian noise standard deviation that can be estimated from the image background [9]. Without patch matching, a “simple averaging” version of (6) is given as

$$\bar{S}(\mathbf{x}_i, \mathbf{q}_k) = \sqrt{\frac{1}{D} \sum_{d=1}^D S^2(\mathbf{x}_i, \mathbf{q}_k; d) - 2\sigma^2}. \quad (7)$$

2.3 Mean Shift

Given a set of diffusion signal profiles $\{S(\mathbf{x}_j, \mathbf{q}_l; d) : (\mathbf{x}_j, \mathbf{q}_l) \in \mathcal{V}_{i,k}, d = 1, \dots, D\}$, we want to determine the modal profile $\tilde{S}(\mathbf{x}_i, \mathbf{q}_k)$. This is achieved using a mean shift algorithm [4] that is modified to take advantage of the patch matching mechanism described above. Mean shift is a non-parametric algorithm for locating the maxima of a density function and is hence a mode-seeking algorithm. It is an iterative algorithm where the mean is progressively updated by using the mean computed in the previous iteration as the reference for computing sample similarity.

We first note that the weights computed using (5) is dependent on the signal vector $\mathbf{S}(\hat{\mathcal{P}})$ of a patch $\hat{\mathcal{P}}$. To explicitly express this dependency, we write $w_{i,k;j,l}(d) := w(\tilde{\mathbf{S}}(\hat{\mathcal{P}}_{i,k}), \mathbf{S}(\hat{\mathcal{P}}_{j,l}(d)))$.

Note that we have made here the mean signal vector $\bar{\mathbf{S}}(\hat{\boldsymbol{\rho}}_{i,k})$ the reference for weight computation. Our implementation of the mean shift algorithm involves the following steps. For iteration $t = 1, 2, \dots, T$,

1. Update weights $w_{i,k;j,l}^{(t)}(d) = w(\bar{\mathbf{S}}^{(t-1)}(\hat{\mathcal{P}}_{i,k}), \mathbf{S}(\hat{\mathcal{P}}_{j,l}(d)))$ based on (5).
2. Update the mean at each location $(\mathbf{x}_j, \mathbf{q}_j)$ using (6) with weights $\{w_{i,k;j,l}^{(t)}(d)\}$ and $\{\mathcal{S}(\mathbf{x}_j, \mathbf{q}_j, d)\}$ for $(\mathbf{x}_j, \mathbf{q}_j) \in \mathcal{V}_{i,k}$.
3. Repeat steps above with $t \leftarrow t + 1$.

3 Experimental Results

Quantitative and qualitative experiments using synthetic and real data were performed to evaluate the proposed method. In all experiments, we set $r_s = 2$ voxels, $\beta = 0.1$, $\alpha_p = 30^\circ$, $\alpha_s = 30^\circ$, and $m = 4$. We use peak signal-to-noise ratio (PSNR) as the metric for performance evaluation.

3.1 Synthetic Data

A synthetic dataset consisting of one- and two-directional fiber bundles was generated for the quantitative evaluation of the proposed method. The dataset was simulated with $b = 1000$ s/mm² and 81 non-collinear gradient directions. In order to simulate the dispersion of fiber orientations across subjects, we generate a set of diffusion signal profiles of fiber bundles oriented according to the Watson probability distribution function [10], which in modified form is given as

$$f(\theta|\kappa) \propto \exp[-\kappa(1 - \cos^2(\theta))], \quad (8)$$

where θ is the angle of deviation from the ground truth direction and the concentration parameter κ is defined as $\kappa = 2(1 - \cos^2(\theta_T))^{-1}$. Parameter θ_T determines the degree of dispersion of the orientations of the fiber bundles. We set $\theta_T = 15^\circ, 30^\circ, 45^\circ$. The fiber orientation distribution functions (ODFs) [11] of some diffusion profiles are shown in Fig. 1. The “atlas” is computed using this distribution of diffusion signal profiles and the outcome is compared with the ground truth without deviation. Four levels of Rician noise (3%, 5%, 7% and 9%) were added to the dataset. Rician noise was simulated by adding Gaussian noise (i.e. $\mathcal{N}(0, \sqrt{p/100})$) to the complex domain of the signal with noise variance determined by noise-level percentage p and maximum signal value v (150 in our case).

As shown in Fig. 2 and Fig. 3, for the various noise levels, our method improves the PSNRs over simple averaging for both cases of one- and two-directional fiber bundles. The PSNR improvement is over 2 dB and sometimes even up to 3 dB. The fiber ODFs of some representative results, shown in Fig. 4, indicate that simple averaging causes artifacts and that the proposed method yields results that are very close to the ground truth.

3.2 Real Data

All images were acquired using a Siemens 3T TRIO MR scanner following a standard imaging protocol: 30 diffusion directions uniformly distributed on a hemisphere, $b = 1,000$ s/mm², one image with no diffusion weighting, 128×128 imaging matrix, voxel size of $2 \times 2 \times 2$ mm³, TE=81 ms, TR=7,618 ms.

As shown in Fig. 5, our method obtains ODFs that are more consistent and exhibit stronger directionality. Visible differences as marked using arrows and boxes. For simple averaging, the ODF glyphs are generally shorter, indicating weaker directionality. In contrast, our method gives sharper and longer ODF glyphs, indicating its superiority.

4 Conclusion

In this paper, we propose a novel patch-based mean-shift algorithm for constructing diffusion MRI atlases. Our method is less sensitive to outliers and is able to deal with inter-subject fiber dispersion. Preliminary experimental results indicate that our method yields improvements over the commonly used simple averaging method and generates diffusion atlases with cleaner fiber orientations and less artifacts caused by inter-subject orientation dispersion.

Acknowledgments

This work was supported in part by NIH grants (NS093842, EB006733, EB009634, AG041721, MH100217, and AA012388) and the National Natural Science Foundation of China (No. 61540047).

References

1. Evans AC, Janke AL, Collins DL, Baillet S. Brain templates and atlases. *Neuroimage*. 2012; 62(2): 911–922. [PubMed: 22248580]
2. Deshpande R, Chang L, Oishi K. Construction and application of human neonatal DTI atlases. *Frontiers in neuroanatomy*. 2015; 9:138. [PubMed: 26578899]
3. Johansen-Berg, H., Behrens, TE. *Diffusion MRI: From quantitative measurement to in vivo neuroanatomy*. Academic Press; 2013.
4. Comaniciu D, Meer P. Mean shift. A robust approach toward feature space analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2002; 24(5):603–619.
5. Buades A, Coll B, Morel JM. A review of image denoising algorithms, with a new one. *Multiscale Modeling & Simulation*. 2005; 4(2):490–530.
6. Wessel, P., Smith, WH. The generic mapping tools. <http://gmt.soest.hawaii.edu>
7. Yap PT, Jiang X, Kot AC. Two-dimensional polar harmonic transforms for invariant image representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2010; 32(7):1259–1270. [PubMed: 20489228]
8. Coupé P, Yger P, Prima S, Hellier P, Kervrann C, Barillot C. An optimized blockwise nonlocal means denoising filter for 3-D magnetic resonance images. *IEEE Transactions on Medical Imaging*. 2008; 27(4):425–441. [PubMed: 18390341]
9. Manjón JV, Carbonell-Caballero J, Lull JJ, García-Martí G, Martí-Bonmatí L, Robles M. MRI denoising using non-local means. *Medical image analysis*. 2008; 12(4):514–523. [PubMed: 18381247]
10. Schwartzman A, Dougherty RF, Taylor JE. False discovery rate analysis of brain diffusion direction maps. *Annals of Applied Statistics*. 2008; 2(1):153–175.

11. Yap PT, Zhang Y, Shen D. Multi-tissue decomposition of diffusion MRI signals via ℓ_0 sparse-group estimation. *IEEE Transactions on Image Processing*. 2016; 25(9):4340–4353.

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

Fig. 1.
Examples from the synthetic dataset simulating (top) one- and (bottom) two-direction fiber bundles.

Fig. 2. PSNR comparison of results given by the mean, computed via simple averaging, and the proposed method for the case of one-direction fiber bundles.

Fig. 3. PSNR comparison of results given by the mean, computed via simple averaging, and the proposed method for the case of two-direction fiber bundles.

Fig. 4.

Comparison of fiber ODFs. (Left) Ground-truth ODFs. (Middle) ODFs given by simple averaging. (Right) ODFs given by the proposed method. The results were generated using synthetic dataset with 9% noise and $\theta_T = 45^\circ$ and 5% noise and $\theta_T = 15^\circ$ respectively for the one- and two-direction cases.

Fig. 5. Comparisons of white matter fiber ODFs given by the simple averaging method (columns 1 and 3) and our method (columns 2 and 4). The fractional anisotropy images at the top are shown for reference. Visible differences between the methods are marked by arrows and boxes.