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Dictionary-based fiber orientation estimation with improved spatial consistency

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ABSTRACT

Diffusion magnetic resonance imaging (dMRI) has enabled *in vivo* investigation of white matter tracts. *Fiber orientation* (FO) estimation is a key step in tract reconstruction and has been a popular research topic in dMRI analysis. In particular, the sparsity assumption has been used in conjunction with a dictionary-based framework to achieve reliable FO estimation with a reduced number of gradient directions. Because image noise can have a deleterious effect on the accuracy of FO estimation, previous works have incorporated spatial consistency of FOs in the dictionary-based framework to improve the estimation. However, because FOs are only indirectly determined from the mixture fractions of dictionary atoms and not modeled as variables in the objective function, these methods do not incorporate FO smoothness directly, and their ability to produce smooth FOs could be limited. In this work, we propose an improvement to *Fiber Orientation Reconstruction using Neighborhood Information* (FORNI), which we call FORNI+; this method estimates FOs in a dictionary-based framework where FO smoothness is better enforced than in FORNI alone. We describe an objective function that explicitly models the actual FOs and the mixture fractions of dictionary atoms. Specifically, it consists of data fidelity between the observed signals and the signals represented by the dictionary, pairwise FO dissimilarity that encourages FO smoothness, and weighted ℓ_1-norm terms that ensure the consistency between the actual FOs and the FO configuration suggested by the dictionary representation. The FOs and mixture fractions are then jointly estimated by minimizing the objective function using an iterative alternating optimization strategy. FORNI+ was evaluated on a simulation phantom, a physical phantom, and real brain dMRI data. In particular, in the real brain dMRI experiment, we have qualitatively and quantitatively evaluated the reproducibility of the proposed method. Results demonstrate that FORNI+ produces FOs with better quality compared with competing methods.

1. Introduction

Diffusion magnetic resonance imaging (dMRI) captures the anisotropic water diffusion in tissue and enables *in vivo* reconstruction of white matter tracts (Johansen-Berg and Behrens, 2013). *Diffusion tensor imaging* (DTI) (Basser et al., 1994) is a basic dMRI strategy that models the water diffusion using a Gaussian distribution, yet it fails to represent crossing fiber tracts. More advanced *high angular resolution diffusion imaging* (HARDI) (Tuch et al., 2002) and *diffusion spectrum imaging* (DSI) (Wedeen et al., 2005) have been proposed to resolve crossing fibers.

The reconstruction of fiber tracts using fiber tracking (Mori et al., 1999; Basser et al., 2000; Reisert et al., 2011) or volumetric tract segmentation (Bazin et al., 2011; Nazem-Zadeh et al., 2011; Yendiki et al., 2011; Ye et al., 2015b) has been applied to many studies on the human brain (Vishwas et al., 2010; Phillips et al., 2009; Catheline et al., 2010). Tract reconstruction requires estimation of *fiber orientations* (FOs) at each voxel. In fiber tracking, the FOs inform the geometry of streamlines that represent the nerve fibers; in volumetric tract segmentation, the FOs are important features that determine the labels of tracts assigned to each voxel. Therefore, the estimation of FOs has been an important research topic in dMRI analysis.

Voxelwise FO estimation algorithms which estimate FOs at each voxel independently were developed first (Behrens et al., 2007; Tournier et al., 2007; Ramirez-Manzanares et al., 2007; Merlet and Deriche, 2013). In particular, dictionary-based FO estimation algo-

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rithms (Ramirez-Manzanares et al., 2007; Aranda et al., 2015; Daducci et al., 2014; Landman et al., 2011; Ye et al., 2015a) have been proposed, where diffusion signals are represented by a dictionary encoded by discretized basis FOs. These methods take advantage of the sparsity of FOs and formulate FO estimation as a sparse reconstruction problem, which could use a lower number of dMRI acquisitions to reconstruct FOs of good quality and thus reduce image acquisition time (Aranda et al., 2015).

Because noise can have a deleterious effect on the accuracy of FO estimation, especially in regions where fibers cross, spatial regularization of FOs has been used to improve FO estimation (Pasternak et al., 2008; Reisert and Kiselev, 2011; Michailovich et al., 2011; Rathi et al., 2014; Auría et al., 2015; Ye et al., 2016). In Michailovich et al. (2011) and Rathi et al. (2014), smoothness of *diffusion weighted images* (DWIs) is added to the spherical ridgelets model, which indirectly promotes FO smoothness. In Reisert and Kiselev (2011) FO continuity is introduced as regularization terms in the spherical harmonics framework. In Pasternak et al. (2008), smoothness of diffusion tensors has been incorporated in the energy function to be minimized. However, sparsity of FOs is not considered in these methods. Other approaches have combined spatial consistency of FOs with FO sparsity in the dictionary-based framework. For example, Auría et al. (2015) and Ye et al. (2016) use weighted ℓ_1-norm regularization to encourage both FO sparsity and spatial consistency. However, in these dictionary-based methods the variables to be estimated are the mixture fractions of dictionary atoms, and FOs are indirectly determined as the basis directions associated with nonzero mixture fractions. The smoothness of FOs is not explicitly incorporated in the objective functions of these methods, which could limit the ability of these methods to produce smooth FOs.

In this work, we reformulate the FO estimation problem so that the regularization of pairwise FO dissimilarity between neighbors can be incorporated into the dictionary-based framework to improve FO estimation. The proposed algorithm is named FORNI+, which stands for an improvement to *Fiber Orientation Reconstruction using Neighborhood Information* (FORNI) (developed in Ye et al. (2016)). We model the diffusion signals by a set of fixed prolate basis tensors. Each basis tensor represents a possible discretized FO, and the dictionary is computed from these basis tensors and the imaging parameters. Instead of using the discretized FOs associated with nonzero mixture fractions of dictionary atoms as the final FO estimates as in previous works (Landman et al., 2012; Ye et al., 2016; Auría et al., 2015), we introduce the use of actual FOs. Then, the actual FOs and mixture fractions of dictionary atoms are explicitly modeled in the objective function, which consists of data fidelity, pairwise FO dissimilarity, and weighted ℓ_1-norm terms that ensure the consistency between the actual FOs and the FO configuration suggested by the mixture fractions. The FOs and mixture fractions are then jointly estimated by minimizing the objective function using an iterative alternating strategy. We applied FORNI+ to a simulation phantom, a physical phantom, and real brain dMRI data. In particular, in the real brain dMRI experiment, we have qualitatively and quantitatively evaluated the reproducibility of the proposed method on five subjects each having two successive scans (10 dMRI scans in total).

The rest of the paper is organized as follows. Section 2 introduces the proposed algorithm for FO estimation. In Section 3, experiments on the phantoms and real brain dMRI are presented. In Section 4, discussion on the results and future work is given, and we summarize the paper in Section 5.

2. Methods

In this section, we first give background on dictionary-based FO estimation and how spatial consistency of FOs has been used to improve FO estimation. Then, we describe the proposed approach that better enforces FO smoothness in the dictionary-based framework, where the design of the objective function and the optimization strategy are presented.

2.1. Background: dictionary-based FO estimation

Diffusion signals can be modeled using a fixed tensor basis (Ramirez-Manzanares et al., 2007; Landman et al., 2012; Ye et al., 2016; Auría et al., 2015), which consists of N prolate tensors $\{\mathbf{D}_i\}_{i=1}^N$ whose primary eigenvectors (PEVs) $\{\boldsymbol{v}_i\}_{i=1}^N$ are approximately evenly distributed over the unit hemisphere and represent possible FOs. The number of the basis tensors can range from about 100 to 300, and in this work we select $N = 289$, which results from successive tessellation of an octahedron. The primary eigenvalues $(\lambda_1 \geq \lambda_2 \geq \lambda_3 > 0)$ of $\mathbf{D}_i$ can be determined by examining the tensors in noncrossing tracts, and λ_2 and λ_3 are set equal (Landman et al., 2012).

Suppose the diffusion signal $S_{k,m}$ at voxel m is associated with a gradient direction $\boldsymbol{g}_k$ and a b-value b_k $(k = 1, \ldots, K)$, and $S_{0,m}$ is the $b0$ signal (where no diffusion gradients are applied) at m. By defining $\boldsymbol{y}_m = (S_{1,m}/S_{0,m}, \ldots, S_{K,m}/S_{0,m})^T$, we have (Landman et al., 2012)

$$\boldsymbol{y}_m = \mathbf{G}\boldsymbol{f}_m + \boldsymbol{\eta}_m, \tag{1}$$

where $\mathbf{G} \in \mathbb{R}^{K\times N}$ is a dictionary matrix with $G_{ki} = e^{-b_k \boldsymbol{g}_k^T \mathbf{D}_i \boldsymbol{g}_k}$, $\boldsymbol{f}_m = (f_{m1}, \ldots, f_{mN})^T$ consists of the unknown nonnegative mixture fractions of dictionary atoms, and $\boldsymbol{\eta}_m$ is a noise term.

Assuming the number of FOs at each voxel is small with respect to the number of gradient directions used in dMRI acquisition, the mixture fractions can be estimated by solving a sparse reconstruction problem (Ramirez-Manzanares et al., 2007; Landman et al., 2012)

$$\hat{\boldsymbol{f}}_m = \underset{\boldsymbol{f}_m \geq \mathbf{0}}{\arg\min} \, ||\mathbf{G}\boldsymbol{f}_m - \boldsymbol{y}_m||_2^2 + \beta||\boldsymbol{f}_m||_1, \tag{2}$$

where β is a weighting constant. Then, basis directions with nonzero mixture fractions can be interpreted as FOs at voxel m. In practice, to account for the effect of noise, only basis directions associated with mixture fractions above a threshold f_{th} (Landman et al., 2012; Ye et al., 2016) are interpreted as FOs

$$\Omega_m = \{\boldsymbol{v}_i | f_{mi} > f_{\text{th}}\}. \tag{3}$$

The choice of the threshold f_{th} has been investigated in Ye et al. (2016), and in this work we follow the suggestions given in Ye et al. (2016) and use $f_{\text{th}} = 0.1$.

The quality of FO estimation can be affected by image noise that is inherent in the acquisition, especially in regions with crossing fibers. Therefore, to improve the accuracy of the estimation, spatial consistency of FOs has been incorporated in the dictionary-based framework. Specifically, Ye et al. (2016) and Auría et al. (2015) replace the ℓ_1-norm with weighted ℓ_1-norm that encodes the interaction between neighbor voxels. For example, in Ye et al. (2016) the problem is formulated as

$$\{\hat{\boldsymbol{f}}_m\}_{m=1}^M = \underset{\boldsymbol{f}_1,\ldots,\boldsymbol{f}_M \geq \mathbf{0}}{\arg\min} \sum_{m=1}^M ||\mathbf{G}\boldsymbol{f}_m - \boldsymbol{y}_m||_2^2 + \beta||\mathbf{C}_m\boldsymbol{f}_m||_1, \tag{4}$$

where M is the total number of voxels and $\mathbf{C}_m$ is a diagonal weighting matrix at m determined by the FOs (suggested by the mixture fractions) in the neighbors. $\mathbf{C}_m$ places small penalties on the mixture fractions associated with basis directions that are consistent with neighbor FOs so that spatial consistency is enforced. Since all the mixture fractions (and thus FOs) are to be estimated and coupled in the weighted ℓ_1-norm, Eq. (4) is solved iteratively using a block coordinate descent strategy.