SPLITTING TRACKING THROUGH CROSSING FIBERS: MULTIDIRECTIONAL Q-BALL TRACKING

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ABSTRACT

We present a new tracking algorithm based on the full multidirectional information of the diffusion orientation distribution function (ODF) estimated from Q-Ball Imaging (QBI). From the ODF, we extract all available maxima and then extend streamline (STR) tracking to allow for splitting in multiple directions (SPLIT-STR). Our new algorithm SPLIT-STR overcomes important limitations of classical diffusion tensor streamline tracking in regions of low anisotropy and regions of fiber crossings. Not only can the tracking propagate through fiber crossings but it can also deal with fibers fanning and branching. SPLIT-STR algorithm is efficient and validated on synthetic data, on a biological phantom and compared against probabilistic tensor tracking on a human brain dataset with known crossing fibers.

Keywords: fiber tractography, diffusion tensor imaging (dti), high angular resolution diffusion imaging (hardi), q-ball imaging (qbi), orientation distribution function (odf).

1. INTRODUCTION

Due to limitations of the Diffusion Tensor (DT) [1] in regions of multiple fiber crossings, classical DT-based tracking algorithms [1, 2, 3] can follow false tracts. These limitations have motivated recent research to generalize the existing diffusion model with new higher resolution acquisition techniques such as Diffusion Spectrum Imaging (DSI) [4], High Angular Resolution Diffusion Imaging (HARDI) [4], and Persistent Angular Structure (PAS)-MRI [5]. These reconstruction techniques have been proposed to define functions having their maximum(a) aligned with the underlying fiber population(s) [6]. For instance, recent probabilistic tractography has been performed using the PAS [5] function and using a HARDI-based model [7] to deal with multiple fiber orientations.

In this paper, we focus on deterministic tractography and use the diffusion orientation distribution function (ODF) from QBI because it is model-free and it can be computed analytically and robustly with low computational cost [6, 8]. Recently, [4, 9] have proposed a generalized streamline (STR) tracking algorithm based on the principal direction of the diffusion ODF computed from DSI. In [10] the definition of streamlines and tensor lines is united and it is used for tractography on a field of high order tensor glyphs. In [11], a multi-tensor local model of the data is used to extend the STR algorithm. Moreover, to deal with more complex fiber configurations, [12] extended streamline tracking with a mixture of Gaussian densities and similarly, [13] recently extended the TEND model with a bi-Gaussian model. Finally, based on the classical diffusion ODF reconstructed from QBI [4] and the very recent regularized version of the diffusion ODF [14], [15] proposes a streamline approach with curvature constraint following all maxima to deal with fibers crossing.

In this paper, we propose another extension to streamline tractography based on the full multidirectional information of the ODF. The principal contribution is to consider the possibility of splitting tracts using *all* available ODF maxima instead of a single direction. Hence, we extend classical streamlines [1, 2, 3] to allow for splitting in multiple directions. The new algorithm is efficient and validated on synthetic data, on a biological phantom and compared against probabilistic tensor tracking on a human brain dataset with known crossing and fanning fibers.

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2. METHODS

2.1. ODF Estimation

Tuch [4] proposed QBI, where the ODF is estimated directly from the raw HARDI measurements on a single sphere by the Funk-Radon transform (FRT). We showed that this FRT could be solved analytically, quickly and robustly [6, 8]. The key idea is to express the HARDI signal as a spherical harmonic (SH) series of order ℓ and to solve the FRT using the Funk-Hecke theorem. The final ODF reconstruction, Ψ, at position p and in direction (θ, ϕ) is

$$\Psi_p(\theta, \phi) = \sum_{k=0}^{\ell} \sum_{m=-k}^{k} 2\pi P_k(0) c_k^m Y_k^m(\theta, \phi), \qquad (1)$$

where Y_k^m denote SH of order k and degree m, c_k^m are the SH coefficients describing the input HARDI signal and P_k is a Legendre polynomial of order k. Note that it is also possible to impose a Laplace-Beltrami regularization criterion while estimating the SH coefficients c_k^m. Here, we use this regularization, which gives more robust fiber detection [6, 8].

2.2. Tracking

We extend the classical streamline techniques [1, 2, 3] based on diffusion tensor principal direction to take into account multiple ODF maxima at each step. We denote $p(s)$ as the curve parameterized by its arc-length. This curve can be computed as a 3D path adapting its tangent orientation locally according to vector field $\mathbf{v}$. Hence, for a given starting point p_0, we solve $p(t) = p_0 + \int_0^t \mathbf{v}(p(s))ds$. The integration is typically performed numerically with Euler or Runge-Kutta schemes of order 2 or 4. In the Euler case, we have the discrete evolution equation

$$p_{n+1} = p_n + \mathbf{v}(p_n)\Delta s, \tag{2}$$

where Δs is a small enough step size to obtain subvoxel precision. A continuous linear, cubic, spline or geodesic [16] interpolation of the vector field can be done at each step for the subvoxel points. For seed point p_0, for a given anisotropy measure A that can be Fractional Anisotropy (FA), Generalized FA (GFA) [4] or any other measure, for anisotropy threshold t_{aniso}, for curvature threshold t_θ, for ExtractMax(Ψ, p) a function returning the list l of vector(s) oriented along each ODF maximum(a) at point p, for size(l) returning the size of list l and for l_j representing the j^{th} element of list l, our algorithm can be described as follows:

(0) Estimate field of ODF, Ψ, with Eq. 1 as in [8]
(1) **Set** seed p_0 and **set** $\mathbf{v}(p_0) = \text{argmax}_{\mathbf{u}} \Psi(\mathbf{u})_{p_0}$
(2) Update curve according to Eq. 2.
    If $A(p_n) < t_{aniso}$ **then** STOP;
    If $\dfrac{\mathbf{v}(p_n) \cdot \mathbf{v}(p_{n-1})}{||\mathbf{v}(p_n)||||\mathbf{v}(p_{n-1})||} > t_\theta$ **then** STOP;
    Let $l = \text{ExtractMax}(\Psi, p_n)$. **If** size($l$) > 1
        then SPLIT curve; **for** $i = 1$ to $|l|$
            do (1) with $p_0 = p_n$ and $\mathbf{v}(p_0) = l_i$;

For the rest of the paper, DT-STR refers to this algorithm using the DT principal eigenvector, ODF-STR refers to this algorithm using a single ODF maxima that is the closest to the incoming tangent direction of the curve, and SPLIT-STR refers to this algorithm using all available ODF maxima.

2.3. Tracking Parameters

DTI estimation is done with least-squares using all diffusion-weighted data altough a more complex and robust estimation method can be used [16]. To extract ODF maxima, it is generally assumed that they are simply given by the local maxima of the normalized ODF ([0,1]), where the function surpasses a certain threshold (here, we use 0.5). We also use $t_{aniso} = 0.15$ for FA in DT-STR and $t_{aniso} = 0.05$ for GFA in ODF-STR and SPLIT-STR, curving angle threshold $t_\theta = 75°$, $\Delta s = 0.1$, classical trilinear interpolation to obtain ODF and DT at subvoxel precision, and Euler integration.

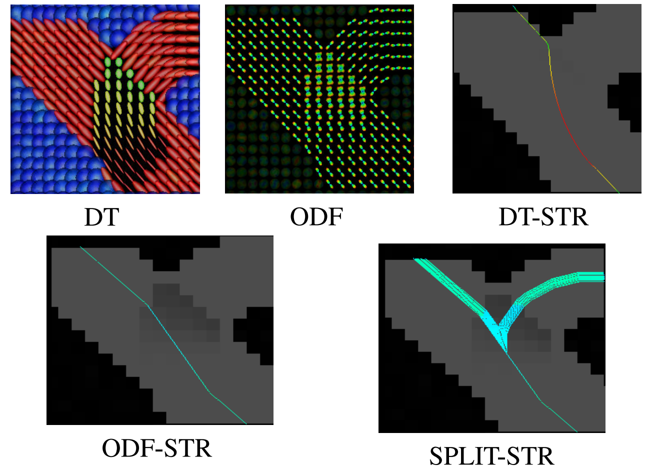

Fig. 1. Tracking on a synthetic branching example.

2.4. Synthetic and Real Data Acquisition

First, we use the multi-tensor model [6, 8] to generate the synthetic data. We generate the diffusion-weighted signal, S, $S(\mathbf{u}_i) = \sum_{k=1}^{2} \frac{1}{2} e^{-b\mathbf{u}_i^{\mathbf{T}}\mathbf{D_k}\mathbf{u}_i} + noise$, where $\mathbf{u}_i$ are the gradient directions on the sphere (a 3^{rd} order tessellation is used), $\mathbf{D_k}$ the k^{th} DT with eigenvalues $[300, 300, 1700]$x10^{-6} mm^2/s (FA $= 0.8$), $b = 3000$ s/mm^2, and noise is generated with a complex Gaussian noise with a standard deviation of $\sigma = 1/35$, producing a signal to noise ratio (SNR) of 35. Then, we use a biological phantom dataset obtained from a 1.5 T scanner with 90 gradient directions and a $b = 3000$ s/mm^2 [17]. Finally, we use a human brain dataset obtained on a 3 T scanner, which has 1.7mm^3 cubic grid and contains 116, 93x93 slices with 60 gradient directions and a $b = 1000$ s/mm^2 [18].

3. RESULTS

Overall, we have two results: 1) SPLIT-STR is able to track through fiber crossings and recover crossing, branching and diverging fiber configurations and 2) SPLIT-STR and ODF-STR are better than DT-STR in regions of fiber crossings because the principal direction followed is more accurate.

Fig. 1 shows the limitations and differences of DT-STR results compared to the ODF-STR and SPLIT-STR results. Tracking was started at the bottom of the branch in all cases. Note that where DTs are prolate with principal direction not agreeing with the true fiber orientations, the ODFs have multiple maxima that match with the underlying fiber population. Hence, the path followed by DT-STR is wrong and follows a false direction that takes it to the middle of the branch. Had there been another structure behind the branching fibers, the

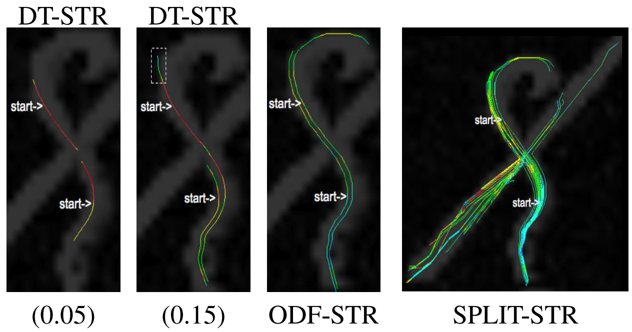

Fig. 2. Tracking on the biological phantom.

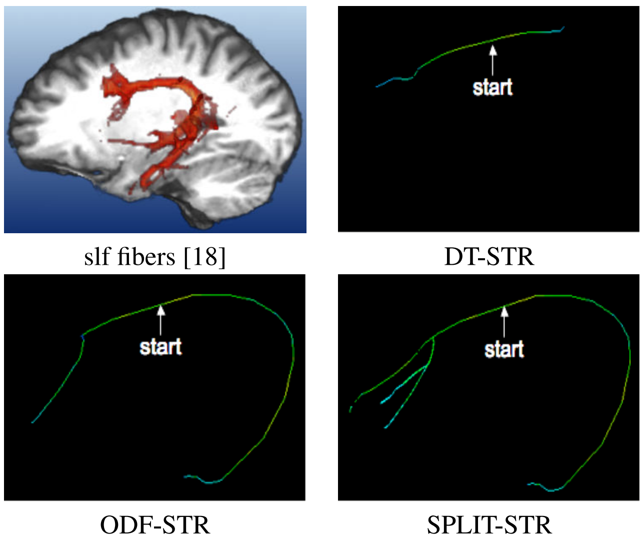

Fig. 3. Tracking of the superior longitudinal fasciculus (slf).

tract could have easily leaked in the other structure and diverged. On the other hand, ODF-STR has the advantage of following the right direction. If there are two possible orientations, it goes in direction closest to its incoming direction. Finally, SPLIT-STR splits and follows both ODF directions when possible which recovers the full branching structure.

Fig. 2 shows that with a conventional FA threshold of 0.15, DT-STR is unable to go through the crossing. Lowering the threshold to 0.05, DT-STR crosses but then steps out of phantom structure in the upper left part of the path. ODF-STR has no problem going through from both initialization seeds and is able to complete a longer part of the tract, even in the high curvature part. Finally, allowing the tracking to split and follow all directions, SPLIT-STR recovers most of the phantom structure.

The top left subfigure of Fig. 3 and 4 are the tracking obtained from probabilistic DT tracking of Anwander et al [18]. They agree with Mori's brain atlas [19]. We use these as gold standard to compare our tracking output. First, in Fig. 3, the tracking is started from only a single seed in the superior longitudinal fasciculus (slf). Note that DT-STR is unable to recover the high curvature part of the fiber whereas ODF-STR can. Moreover, SPLIT-STR can recover the splitting part at the end of the slf. Then, in Fig. 4, the tracking is started from four voxel seeds in the anterior thamalic radiation (tr). As expected, DT-STR stops in the area of high complexity whereas ODF-STR is able to step through the crossings and recover the posterior tr and corticopontine tract. Again, SPLIT-STR is able to recover more by also splitting into the superior tr. Overall, SPLIT-STR results qualitatively agree with the gold standard and known cerebral anatomy.

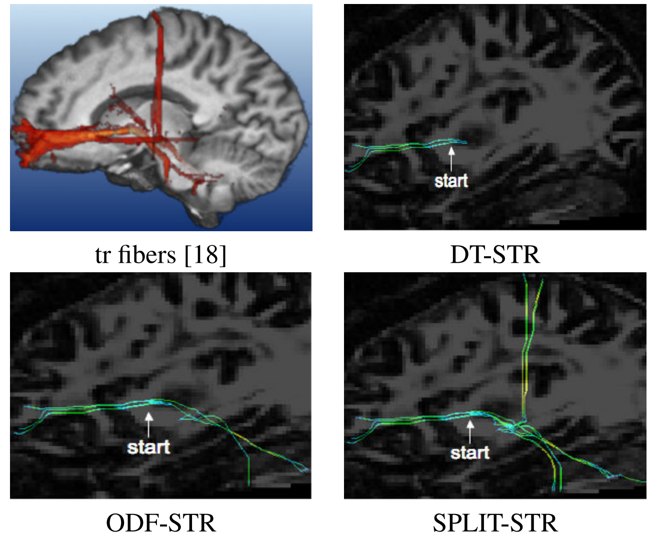

Fig. 4. Tracking of the thamalic radiations (tr).

4. DISCUSSION

We have introduced SPLIT-STR, a new q-ball multidirectional tracking algorithm using all available ODF maxima. First, we showed that choosing the principal direction of the ODF improves tracking results in regions of crossing when compared with the principal direction of the DT. It stops the tracking from taking false directions. Second, by allowing tracts to split SPLIT-STR recovers more complete fiber bundles. It is thus possible to track fibers crossing and fanning. We have validated and compared our results on bundles where tracts were known in synthetic data, in a biological phantom and in a brain dataset. However, more validation could be performed on real data. This is a difficult problem with human white matter as there is no ground truth.

Other questions remain for multidirectional tractography: Should the tracking algorithm split as much as possible to recover as much fiber structure as possible before clustering and post-processing the tracts to separate them into bundles? Or, should the tracking have a built-in scheme to differentiate the different sub-voxel crossing possibilities and decide whether or not a tract should be split? For instance, split in the case of a branching bundle but not split in the case of a crossing fiber because then it steps into a different fiber bundle. The problem of chosing the best spliting strategy could benefit from any a priori information on the local geometry of the fibers.

Overall, SPLIT-STR overcomes limitations of DT-STR in regions of low anisotropy and regions of crossing fibers. To our knowledge, it is the first tracking method to use all available direction estimates from q-ball data at each step. We are thus able to recover large amount of fiber bundles with complex tissue architecture starting from only a few seed points. Moreover, since ODFs are reconstructed from a fast and robust analytical QBI method, the algorithm is reliable with a low computational cost. It is now important to look into probabilistic tracking algorithm based on the full ODF to remove the intermediate step of extracting ODF maxima.

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