Online Filtering Tractography: Tracking with anatomical priors

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INTRODUCTION: This abstract investigates how the mask affects streamline tractography. The discrete binary mask is an aggressive stopping criterion that can result in a large proportion of prematurely stopping streamlines [1]. Recently, Smith *et. al* [2]. proposed a method called Anatomically Constrained Tractography, which interpolates partial volume fraction maps based on the structural T1-weighted image and uses thresholds to determine when to include or to exclude the streamline. We propose a method called Online Filtering Tractography (OFT) which is an extension of the modular Sequential Monte Carlo Tractography [3]. OFT propagates simultaneously multiple streamlines using the full partial volume fraction maps to enforce the tracking in the white matter (WM) and stop in gray matter (GM). Streamlines propagating in cerebrospinal fluid (CSF) partial volume fraction map are iteratively repressed. Results of OFT using partial volume fraction maps overcome some limits of tracking with binary mask.

METHODS: Streamline tractography can be modeled as a state system connected over time by a Markov chain. States **x=(p, v, s)** are the 3D position **p**, the previous tracking direction **v** and the tracking status **s** □ {*active* (in the WM), *inactive* (stopped in the GM)}. We propose to use a particle filter [3, 4] to estimate a sequence of target state variables $\mathbf{X_{0:T}=\{X_k : k}$ □ $\mathbf{\{0,...,T\}\}}$ from a sequence of observation variables $\mathbf{Y_{0:T} =\{Y_k :}$ $\mathbf{k}$ □ $\mathbf{\{0,...,T\}\}}$, where $\mathbf{T=\Delta t \cdot \delta_{max}}$ is the total process time (with $\mathbf{\delta_{max}}$ the maximum length and $\mathbf{\Delta t}$ the step size). In the proposed model, observations are the likelihood of the streamline to be at position **p**. $\mathbf{\{(x_k^{(i)}, w_k^{(i)}) : i}$ □ $\mathbf{\{1,\ldots,N\}}$ denotes the set of **N** discrete random samples that characterize the posterior distribution, where $\mathbf{x_k^{(i)}}$ is a random samples **i** at time **k** and $\mathbf{w_k^{(i)}}$ its associated weights (with $\Sigma_i\, \mathbf{w_k^{(i)}}$=1). The transition function between two states is defined by a streamline probabilistic tractography algorithm [3,5]. In the current implementation we chose the fiber orientation distribution function (fODF) reconstruction [5, 6]. The transition at state $\mathbf{x_k^{(i)}}$ corresponds to a step $\mathbf{\Delta t}$=0.2mm in a direction within aperture cone of the previous tracking direction **v** (based on a minimum radius of curvature **R**=1mm [6]). A direction is drawn according to value of the fODF at **p**. This transition occur if **s**=*active* otherwise $\mathbf{x_{k+1}^{(i)} = x_k^{(i)}}$. All samples are initiated with **s**=*active*, **s** becomes inactive when **p** reach the GM. **v** is initiated randomly according to the fODF at **p.**

OFT weights samples $\mathbf{x_k^{(i)}}$ based on the likelihood of the position **p** of a propagating streamline. This prior is encapsulated in a 3D map called the exclusion map **E**, which allows the use of the partial volume fraction map of CSF. Specific regions of **E** can then be set to 1 following binary filters, blocking the propagation of streamlines in these regions. The weight $\mathbf{w_k^{(i)}}$ of a sample $\mathbf{x_k^{(i)}}$ is set following **Equation 1**. Such a discrete model suffers of degeneracy since the variance of the weights increases over time, leading to a situation where all samples except one have a weight close to zero. To overcome this problem, a resampling method is apply when a significant degeneracy is observed (when the number of effective samples $\mathbf{N_{eff}}$ = 1 / $\Sigma_i\, (\mathbf{w_k^{(i)}})^2$ is below the threshold $\mathbf{N_T}$=**N**/2 [4]). The resampling eliminates samples with small weights and concentrates on samples with large weights. The resampling generates **N** new samples with equal weights from the current discrete estimation of $\mathbf{X_k}$.

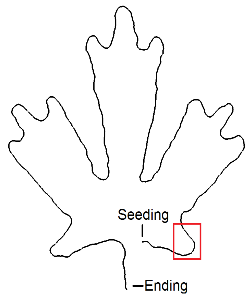

Figure 1. A streamline of the final distribution using OFT on synthetic data [7].

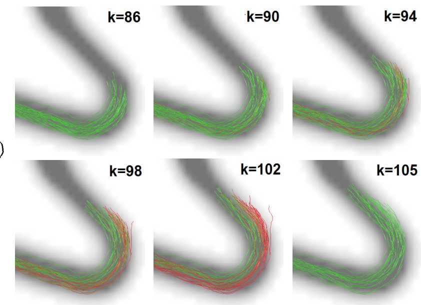

Figure 2. OFT samples propagation and resampling (k=105) steps on synthetic data [7]. Reddish streamlines have lower weight.

$$w_k^{(i)} = w_{k-1}^{(i)} \cdot \begin{cases} 0 \text{ If } s = active \text{ and there is no valid tracking direction,} \\ 0 \text{ If } s = inactive \text{ and, } k \cdot \Delta t < \delta_{min} \text{ or } k \cdot \Delta t > \delta_{max}, \\ 1 - E(p) \text{ otherwise.} \end{cases}$$

Equation 1. The weighting function. $\mathbf{\delta_{min}}$ is the minimum length and $\mathbf{\delta_{max}}$ is the maximum length of a streamline.

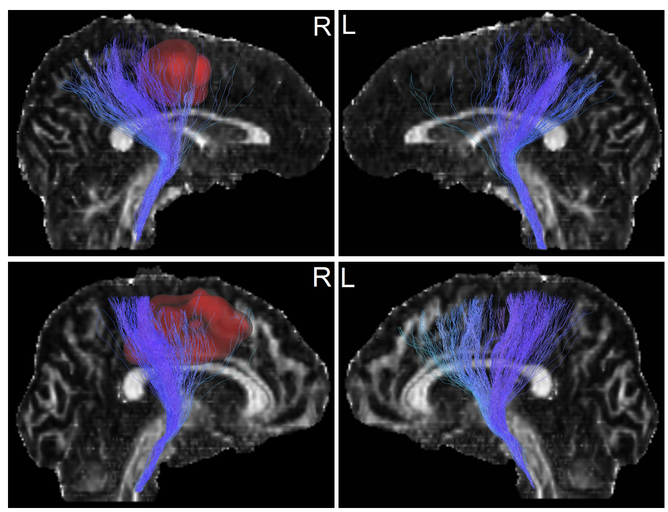

Figure 3. CST approximation using OFT. Top row subject 1, bottom row subject 2 of the *MICCAI DTI Tractography Challenge 2012* [8,10]. The red surfaces show tumors and a middle sagittal slice is shown as reference.

DATASET: We show results on the maple leaf synthetic dataset from the *Common DTI Dataset* [7] (30 directions, b=1000 s/mm^2, SNR=14). We estimated the fODFs using de MRtrix [5] software. Results are also shown on human brain data from the *MICCAI DTI Tractography Challenge 2012* [8,10] (31 directions, b=1000 s/mm^2). The fODFs were estimated using spherical deconvolution [6]. The partial volume maps were calculated using FSL/FAST [9].

RESULTS AND DISCUSSION: Figure 1 shows a streamline (**N**=1000) obtained using OFT on the complex noisy maple leaf data. Since we do not have access to a CSF map, we used the synthetic T2-weighted image as **E** map. This example shows how anatomical priors on streamlines can be used to achieve a better approximation. Reconstructing the full maple leaf is not possible even using several thousand seeds with the same tractography algorithm. **Figure 2** presents the OFT process. Streamlines are weighted until resampling takes place. The curvature configuration makes some streamlines stop prematurely, which are removed by the resampling. **Figure 3** presents 1000 streamlines of the corticospinal tract (CST) obtained using OFT (**N**=10000). The **E** map was the CSF map. Additionally, we selected an axial slice where the left and the right cerebral peduncles were visible and set to 1 all other voxels of the slice in the **E** maps (see **Figure 4**). The seeding was done in lower part of the CST in the acquired images, streamlines propagating toward the spinal cord were stop by a binary filter (see **Figure 4**). In order to generate the left and the right CST independently, we set to 1 voxels in the **E** map of an axial slice just above the seeding region to block the propagation of streamlines in the opposite CST. Anatomical priors were shown to be crucial [10] to approximate an accurate CST without all spurious streamline to the cerebellum and rest of the brain. OFT using the CSF map as **E** map combined to binary segmentation provided qualitatively the best CST approximation [10]. Differences can be observed between the healthy and the tumor side on both subjects, possibly due to the presence of the tumor.

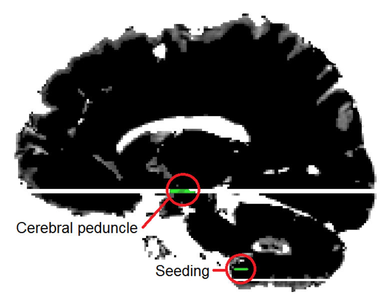

Figure 4. The E map of subject 2.

Other priors could be used to inform tractography of plausible pathways, such as probabilistic tract atlas or probabilistic regions segmentation. Also, other probabilistic algorithm could be used in the propagation step of OFT. However, since priors are used in the tractography algorithm, interpretation of the streamlines is done based on the **E** map, and as any streamline interpretation, must be done with care. Nevertheless, we think OFT opens a new way to incorporate priors on the structural position of streamlines and use it within the tractography algorithm to filter spurious streamlines and provide more realistic approximations.

REFERENCES: [1] Cote *et al.* (2012) MICCAI, [2] Smith *et al.* (2012) NeuroImage, [3] Girard and Descoteaux (2012) MICCAI: CDMRI, [4] Arulampalam *et al.* (2002) IEEE Transactions on Signal Processing, [5] Tournier *et al.* (2012) International Journal of Imaging Systems and Technology [6] Descoteaux *et al.* (2009) IEEE transactions on medical imaging, [7] Common DTI Dataset, url: cubric.psych.cf.ac.uk/commondti, [8] MICCAI DTI Challenge 2012, url: dti-challenge.org, [9] Zhang et al. (2001) IEEE transactions on medical imaging, [10] Girard *et al.* (2012) MICCAI: DTI Challenge.