REINFORCEMENT TRACTOGRAPHY: A HYBRID APPROACH FOR ROBUST SEGMENTATION OF COMPLEX FIBER BUNDLES

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ABSTRACT

We develop and evaluate a novel hybrid tractography algorithm for improved segmentation of complex fiber bundles from diffusion magnetic resonance imaging datasets. We propose an approach inspired by reinforcement learning that combines the strengths of both probabilistic and deterministic tractography to better resolve pathways dominated by crossing fibers. Given a fiber bundle query, our approach first explores an array of possible pathways probabilistically, and then exploits this information with streamline tractography using globally optimal fiber compartment assignment in a conditional random field. We quantitatively evaluated our approach in comparison with deterministic and probabilistic approaches using a realistic phantom with Tractometer and 88 test-retest scans from the Human Connectome Project. We found that the proposed hybrid method offers improved accuracy with phantom data and more biologically plausible topographic organization and higher reliability with in vivo data. This demonstrates the benefits of combining tractography approaches and indicates opportunities for integrating reinforcement learning strategies into tractograpy algorithms.

Index Terms— tractography, diffusion MRI, acoustic radiations, reinforcement learning, machine learning

1. INTRODUCTION

Tractography is the only non-invasive method for reconstructing brain fiber bundle pathways in vivo, which makes it a valuable scientific tool for neuroscience research and biomedical applications [1]. One of its goals is to produce mathematical models of fiber bundles from coherent patterns of fiber orientations obtained from diffusion magnetic resonance imaging (dMRI) data; however, this is complicated by the presence of crossing fibers, partial volume effects, and inherent ambiguities as an inverse problem [2] [1]. Learning-based approaches are emerging as a practical solution for segmenting fiber bundles across subjects [3]; however, classical tractography approaches are still essential for generating high fidelity training data and for analyzing individual and unusual cases, e.g. ex-vivo scans, non-human subjects, surgical cases, etc. Most existing classical solutions can be broadly categorized as deterministic, probabilistic, or global [1], with each having distinct performance characteristics with respect to anatomical accuracy, false positive rate, computational cost, and ability to find complex connections [4] [5] [2]. As there exist distinct strengths and weaknesses of modern tractography algorithms [6], there is an opportunity for making better methods by deriving hybrid algorithms that leverage the relative advantages of these different approaches.

This paper investigates a novel hybrid tractography algorithm that takes inspiration from reinforcement learning to improve the reconstruction of fiber bundles dominated by crossing fibers. We propose a multi-stage approach that uses a reinforcement learning strategy of exploitation and exploration. For given a fiber bundle query, our algorithm first explores the array of possible pathways probabilistically, and then exploits this information with streamline tractography using globally optimal fiber compartment assignment. We formulate the compartment assignment problem using a conditional random field guided by prior probabilistic tracking with a spatial smoothness criteria. We evaluated our proposed approach using a realistic digital phantom and compared its performance to existing approaches using Tractometer, and we also applied the method to the reconstruction of the acoustic radiations in a large cohort of high quality in vivo scans to assess its biological plausibility, robustness to variation in brain morphometry, and scan-rescan reliability.

2. METHODS

The primary goal of this work is to investigate how probabilistic and deterministic tractography algorithms can be hybridized to improve their performance. Reinforcement learning offers motivation for pursuing this idea, as we observe that probabilistic and deterministic tracking map reasonably well onto the exploration and exploitation stages that drive such systems. Generally speaking, the exploration stage involves the gathering of information that may be useful for solving a given problem, and the exploitation phase makes the best decision possible with the information at hand. These steps are typically iterated in one of a variety of schemes, but here,

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Fig. 1. An illustration of the proposed hybrid tractography algorithm showing the input query and image data and stages for exploitation and exploration. The shown data depict the corticospinal tract from the ISMRM 2015 Tractography Challenge

we consider something akin to an epsilon-first strategy [7], in which a single pass of exploration and exploitation is taken.

We have developed this plan into a hybrid tractography algorithm that bridges probabilistic and deterministic approaches with a framework for optimal compartment selection. The workflow takes a fiber bundle query, in the form of typical inclusion and exclusion masks, and makes a simplifying assumption that each voxel contains a single optimal compartment that represents the given bundle. Our experiments used the multi-fiber ball-and-sticks diffusion model [8] implemented in FSL; however, an analogous workflow could be implemented using peak orientations and amplitudes from fiber orientation distributions. Our methods and experiments were implemented in the Quantitative Imaging Toolkit (QIT) $[9]^{1/2}$. We denote the set of voxels of the image volume as \mathcal{V} with arbitrary individual voxels p and q, where each voxel p contains up to K fiber compartments that are parameterized by a fiber orientation v_p^k and volume fraction f_p^k . The number of compartments K is determined during diffusion model fitting, and the volume fractions are expected to be positive and have a sum less than or equal to one, to permit the modeling of free water. A label map L for a given bundle represents the index of the optimal compartment in each voxel, with $L_p \in [0, 1, ..., K]$, with zero indicating no match. The algorithm is illustrated in Figure 1 and described below.

2.1. Exploration

A primary advantage of probabilistic tractography is its ability to explore a wide range of possible pathways through its repeated application [8]. This is unlike deterministic tracking, which uses a restricted set of directions for propagating streamlines that match the nearest principal fiber orientation [10]. On the other hand, probabilistic tracks can also take a tortuous route in forming connections, creating disorganized bundle reconstructions and possibly taking invalid paths. However, we have observed that the voxel-wise aver-

¹http://cabeen.io/qitwiki

age of orientations of dense probabilistic tracks are far more organized than the tracks themselves, and thus, they offer an avenue for tractography refinement. These factors motivated our use of probabilistic tracking in a first stage of our hybridized pipeline, in which the goal is to explore a wide array of possible paths that form the bundle being queried. We use the following tracking parameters: a large angle threshold of 85 degrees; dense seeding with 10 seeds per voxel; a minimum volume fraction of 0.075; random sampling of fiber orientations around peaks directions with a fixed standard deviation of 0.15 [3], and track filtering to meet the fiber bundle query criteria. We finally compute a tract orientation map [3] to summarize the most likely orientation μ_p of the probabilistic tracks passing through voxel p and retain it for use as a prior on the optimal compartment in the exploitation stage, which is described next.

2.2. Exploitation

The algorithm then aims to exploit the information gained through probabilistic tracking by first estimating the optimal fiber compartment for each voxel that best represents the queried bundle and then subsequently reconstructing it with streamline integration. We frame the compartment assignment problem as inference on Bayesian graphical model with priors based on the probabilistic tract orientation map and spatial smoothness. Specifically, we build a conditional random field (CRF) [11] whose minimal energy state (E) corresponds to the optimal compartment labeling L:

$$E(L) = \sum_{p \in \mathcal{V}} U_p(L_p) + \gamma \sum_{(p,q) \in \mathcal{N}} V_{pq}(L_p, L_q)$$
(1)

which is the sum of terms for unary (U) and pairwise (V) potentials. The unary potential gives preference to compartments that match the tract orientation map, $U_p(k) = 1 - |v_p^k \cdot \mu_p|^2$, and the pairwise potential gives preference to orientationally aligned compartments, $V_{pq}(a, b) = 1 - |v_p^a \cdot v_q^b|^2$. The pairwise potential is defined over the possible pairs from

²https://resource.loni.usc.edu/resources/downloads

6-neighborhoods \mathbb{N} , and γ is a hyperparameter controlling the spatial smoothness. We initialize with the compartments nearest to μ_p within the bundle and optimize the CRF with the iterated conditional modes algorithm until convergence. Once the optimal compartments are found, all others are excluded, and streamline tractography is performed with similar parameters as those used in the exploration stage [10], and the final bundle is obtained by applying the bundle query criteria.

3. EXPERIMENTS AND RESULTS

We evaluated the proposed hybrid tractography algorithm and compared its performance to typical deterministic and probabilistic approaches using a realistic digital phantom and an application to modeling the acoustic radiations.

3.1. Evaluation with a realistic phantom

Our first experiment used a realistic digital phantom from the 2015 ISMRM tractography challenge [2]. Briefly, this phantom was created by creating 25 ground truth bundles from in vivo human dMRI data and then synthesizing a digital dMRI phantom depicting only these bundles. Our experiments used distinct inclusion masks for each bundle to represent the cortical and subcortical brain areas connected by each bundle. We ran deterministic, probabilistic, and the proposed hybrid tractography using these inclusion masks as bundle query criteria. We controlled the experiment by using identical tracking parameters and matching seedpoints, which were precomputed with 10 samples per voxel. Tractography was implemented in QIT and the probabilistic and determinisitic conditions matched the analogous parts of the hybrid tractography algorithm. We measured performance relative to the ground truth bundles using the standalone implementation of Tractometer [12], which provides the following metrics: invalid connections (IC), valid connections (VC), no connections (NC), spatial agreement (F1), and fiber count (FC). Our results are reported in Table 1.

3.2. Evaluation with the acoustic radiations

We further evaluated our approach through an evaluation of the reconstruction of the acoustic radiations (AR). The AR are a component of the auditory pathway that relays information from the medial geniculate nucleus to primary auditory cortex on the transverse temporal gyrus. The AR crosses substantial vertical thalamic and longitudinal pathways that complicate AR reconstruction, but comparisons with blunt micro-dissections have shown some promise of probabilistic tractography in AR modeling [13]. However, Maffei et al. also observed notable issues such as noisy model geometry and numerous false positives, which impact the anatomical plausibility of AR models made with probabilistic tracking. Tractography models with topographic regularity are potentially valuable [14], so we chose the AR as test case for our approach; furthermore, we included an additional evaluation metric to measure topographic regularity as a gauge of anatomical plausibility. We computed the endpoint correlation (EC), a simple index of bundle coherency, with the following procedure: orient the bundle to have consistent starts and ends, sample 5000 pairs of tracks, compute the distances between each pair for both the starts and ends, and finally compute the Pearson correlation coefficient between corresponding endpoint distances. A high EC would indicate that the pattern of inter-curve distances at the start of the bundle is statistically similar to the corresponding ones at the end, thus preserving some basic level of topographic organization.

Our experiments examined AR reconstruction using data from the Human Connectome Project (HCP) [15] with approval from the USC institutional review board. We used an atlas-based approach to query the AR, with inclusion ROIs that were manually drawn to match the expected beginning and end of the left and right AR. To ensure consistent seeding conditions when comparing methods, 10000 seed points were sampled per bundle in atlas space. We deformed these inclusion masks and seed points from the group template to each subject's native space using DTI-TK [16], and we compared deterministic and probabilistic approaches to the proposed hybrid tractography algorithm using identical tracking parameters to the previous experiment. We extracted the left and right AR from 88 scans comprising the test-rest portion of the HCP data, and we measured the EC and three measures of scan-rescan reproducibilty. Specifically, we looked at the coefficient of variation (CV) of the total bundle volumes, and following intra-subject registration, we measured the voxelwise spatial agreement using both the standard and weighted forms of the Dice coefficient [17]. The resulting AR models are shown in Figure 2 and are plotted in Figure 3.

Table 1. Tractometer and topographic regularity results comparing the performance of the hybrid approach with standard deterministic and probabilistic approaches, which were run under identical tracking, seeding, and selection criteria.

Method	IC	VC	NC	F1	EC	FC
Probab.	17%	83%	0.5%	65%	9%	4977
Determ.	17%	83%	0.5%	65%	10%	5197
Hybrid	13%	86%	0.3%	67%	22%	8574

4. DISCUSSION AND CONCLUSIONS

Our results demonstrate a number of benefits of the proposed hybrid tractography approach. In particular, the Tractometer results show a consistent improvement in reconstruction ac-



Fig. 2. Qualitative comparison of tractography results from modeling the acoustic radiations in HCP.



Fig. 3. Quantitative tractography results from modeling the acoustic radiations in HCP data, comparing deterministic (Det) and probabilistic (Prob) tracking with the proposed method (Hybrid) in terms of topography and reproducibility.

curacy across the phantom fiber bundles, as evidenced by increased valid connections and the F1 spatial agreement measure, as well as decreased invalid and incomplete connections (Table 1). Furthermore, our analysis of the AR demonstrated how the proposed refinforcement tractography algorithm can produce more biologically plausible, i.e. topographically coherent, bundles with robustness to changes in brain morphometry across typical changes across a typical adult population. The AR is a valuable test case, as it includes sharp turns, fanning, and a substantial crossings with longitudinal and projection pathways (Fig. 2). Our quantitative analysis showed that the proposed hybrid method provides greater reliability than either deterministic or probabilistic tracking alone, as shown by a lower volume CV and higher dice scores (Fig. 3). Our approach makes a simplifying assumption of a single compartment per voxel, and the results lend some support to this assumption as a useful simplification for improving tracking. Furthermore, our results showed that, under identical seeding conditions, the proposed approach included a greater proportion of the seeds in the final bundle, suggesting some measure of greater efficiency.

It should be noted that there are, of course, other probabilistic and deterministic tracking algorithms than tested here, and a more extensive evaluation would be required to draw broad conclusions regarding the relative performance of hybridized tractography. However, the experimental design of our evaluation was tightly controlled for potential confounds, such as software implementation, seed placement, and tracking parameters, so what we can conclude is that the hybridization of probabilistic and deterministic approaches is indeed a useful and promising direction for improving tractography methods. Furthermore, the framework of reinforcement learning may prove to be a fruitful direction for such approaches. We explored a basic system here, but it demonstrates how probabilistic and deterministic approaches map logically onto exploration and exploitation schemes. We used optimal compartment assignment as a way to bridge these two, but there are possibly other interesting and valuable intermediates.

In summary, we have presented a novel hybrid tractography algorithm that is designed with inspiration from reinforcement learning to leverage the strengths of both probabilistic and deterministic tractography algorithms through distinct stages for exploration and exploitation. Our experiments indicate that such a hybrid approach offers benefits for the reconstruction of complex fiber bundles that are dominated by crossing fibers, such as the acoustic radiations. In particular, the resulting fiber bundle models tend to have fewer false positive tracks and greater topographic coherence. This demonstrates the benefits of combining tractography approaches, and it highlights the opportunities ahead for integrating reinforcement learning strategies into tractography algorithms. Our implementation is available online as part of the Quantitative Imaging Toolkit.

5. REFERENCES

- Ben Jeurissen, Maxime Descoteaux, Susumu Mori, and Alexander Leemans, "Diffusion mri fiber tractography of the brain," *NMR in Biomedicine*, vol. 32, no. 4, pp. e3785, 2019.
- [2] Klaus H Maier-Hein, Peter F Neher, Jean-Christophe Houde, Marc-Alexandre Côté, Eleftherios Garyfallidis, Jidan Zhong, Maxime Chamberland, Fang-Cheng Yeh, Ying-Chia Lin, Qing Ji, et al., "The challenge of mapping the human connectome based on diffusion tractography," *Nature communications*, vol. 8, no. 1, pp. 1349, 2017.
- [3] Jakob Wasserthal, Peter F. Neher, Dusan Hirjak, and Klaus H. Maier-Hein, "Combined tract segmentation and orientation mapping for bundle-specific tractography," *Medical Image Analysis*, vol. 58, pp. 101559, 2019.
- [4] Sonia Pujol, William Wells, Carlo Pierpaoli, Caroline Brun, James Gee, Guang Cheng, Baba Vemuri, Olivier Commowick, Sylvain Prima, Aymeric Stamm, et al., "The dti challenge: toward standardized evaluation of diffusion tensor imaging tractography for neurosurgery," *Journal of Neuroimaging*, vol. 25, no. 6, pp. 875–882, 2015.
- [5] Vishwesh Nath, Kurt G Schilling, Prasanna Parvathaneni, Yuankai Huo, Justin A Blaber, Allison E Hainline, Muhamed Barakovic, David Romascano, Jonathan Rafael-Patino, Matteo Frigo, et al., "Tractography reproducibility challenge with empirical data (traced): The 2017 ismrm diffusion study group challenge," *Journal of Magnetic Resonance Imaging*, 2019.
- [6] Kurt G Schilling, Vishwesh Nath, Colin Hansen, Prasanna Parvathaneni, Justin Blaber, Yurui Gao, Peter Neher, Dogu Baran Aydogan, Yonggang Shi, Mario Ocampo-Pineda, et al., "Limits to anatomical accuracy of diffusion tractography using modern approaches," *NeuroImage*, vol. 185, pp. 1–11, 2019.
- [7] Long Tran-Thanh, Archie Chapman, Enrique Munoz de Cote, Alex Rogers, and Nicholas R Jennings, "Epsilon–first policies for budget–limited multi-armed bandits," in *Twenty-Fourth AAAI Conference on Artificial Intelligence*, 2010.
- [8] Timothy EJ Behrens, H Johansen Berg, Saad Jbabdi, Matthew FS Rushworth, and Mark W Woolrich, "Probabilistic diffusion tractography with multiple fibre orientations: What can we gain?," *NeuroImage*, vol. 34, no. 1, pp. 144–155, 2007.

- [9] Ryan P Cabeen, David H Laidlaw, and Arthur W Toga, "Quantitative Imaging Toolkit: Software for Interactive 3D Visualization, Processing, and Analysis of Neuroimaging Datasets," in *Proc Intl Soc Mag Reson Med*, 2018, number 2854.
- [10] Ryan P Cabeen, Mark E Bastin, and David H Laidlaw, "Kernel regression estimation of fiber orientation mixtures in diffusion MRI," *NeuroImage*, vol. 127, pp. 158– 172, 2016.
- [11] John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira, "Conditional random fields: Probabilistic models for segmenting and labeling sequence data," in *Proceedings of the Eighteenth International Conference on Machine Learning*, San Francisco, CA, USA, 2001, ICML '01, pp. 282–289, Morgan Kaufmann Publishers Inc.
- [12] Marc-Alexandre Côté, Gabriel Girard, Arnaud Boré, Eleftherios Garyfallidis, Jean-Christophe Houde, and Maxime Descoteaux, "Tractometer: towards validation of tractography pipelines," *Medical image analysis*, vol. 17, no. 7, pp. 844–857, 2013.
- [13] Chiara Maffei, Jorge Jovicich, Alessandro De Benedictis, Francesco Corsini, Mattia Barbareschi, Franco Chioffi, and Silvio Sarubbo, "Topography of the human acoustic radiation as revealed by ex vivo fibers micro-dissection and in vivo diffusion-based tractography," *Brain Structure and Function*, vol. 223, no. 1, pp. 449–459, 2018.
- [14] Dogu Baran Aydogan and Yonggang Shi, "Tracking and validation techniques for topographically organized tractography," *NeuroImage*, vol. 181, pp. 64–84, 2018.
- [15] Stamatios N Sotiropoulos, Saad Jbabdi, Junqian Xu, Jesper L Andersson, Steen Moeller, Edward J Auerbach, Matthew F Glasser, Moises Hernandez, Guillermo Sapiro, Mark Jenkinson, et al., "Advances in diffusion mri acquisition and processing in the human connectome project," *NeuroImage*, vol. 80, pp. 125–143, 2013.
- [16] Hui Zhang, Paul A Yushkevich, Daniel C Alexander, and James C Gee, "Deformable registration of diffusion tensor mr images with explicit orientation optimization," *Medical image analysis*, vol. 10, no. 5, pp. 764–785, 2006.
- [17] Martin Cousineau, Pierre-Marc Jodoin, Eleftherios Garyfallidis, Marc-Alexandre Côté, Félix C Morency, Verena Rozanski, Marilyn GrandMaison, Barry J Bedell, and Maxime Descoteaux, "A test-retest study on parkinson's ppmi dataset yields statistically significant white matter fascicles," *NeuroImage: Clinical*, vol. 16, pp. 222–233, 2017.