TRACTOGRAPHY USING REINFORCEMENT LEARNING AND ADAPTIVE-EXPANDING GRAPHS

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ABSTRACT

Diffusion MRI provides useful information about the directional structure of sub-cortical white matter non-invasively. Reconstruction methods generate fiber directions at each voxel which become inputs of tracking algorithms. However, current evidence shows that none of existing tracking algorithms generate accurate tractography free of invalid bundles. In this work, we reformulate the problem of tracking as a reinforcement learning problem. We have built a framework that accepts fiber directions but allows to find a bundle between a starting ROI and a goal ROI provided by the user. The proposed framework is able to store the past exploration and update its belief, and finally make its decision of choosing which way to go based on its learned knowledge. Such property is achieved by a novel design that integrates the reinforcement learning mechanism and an adaptive-expanding tree structure that explores, and learns from different scenarios.

Index Terms— Tractography, reinforcement learning

1. INTRODUCTION

Given the great number of voxels with partial volume effects and crossings in the brain we have to be very careful in constructing tracking algorithms [1–4]. To date, researchers have introduced three main types of fiber tracking: deterministic, probabilistic, and global. However, none of these techniques have managed to resolve the number of invalid tracks or other major issues, see [1, 3].

In our study, we propose a new tracking strategy based on Reinforcement Learning (RL). We are inspired by the RL framework due to its nice rewarding mechanism which reinforces the "correct" behavior whereas discourages those "incorrect" actions while it is exploring an unknown environment – here the space of diffusion directions. To address this problem, we provide a design on top of RL and extend it by combining it with an efficient exploration algorithm.

2. METHOD

We extend RL by integrating a expanding-tree data structure and exploration algorithm, so that our tracker expands the tree during its exploration. The belief of the tracker is also updated and represents its knowledge learned from past experience (see Fig. 1). The tree grows adaptively during the exploration, and the agent learns and updates its belief on the pathways using Temporal Difference learning:$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$, where $V(S_t)$ is the value for state S_t (tree node – relates to track point) at time t , and R_t is step reward at time t in state S_t. Constant $\gamma \in (0, 1)$ is a discount rate and α is the learning rate. Each tree node maintains values of reward and belief learned so far along the path. The optimal path can be extracted using the reward values (e.g., the red path in Fig. 1). The system is adaptively learning the state values. Our method can figure out if a bundle should cross or turn which is currently a hard issue with existing methods.

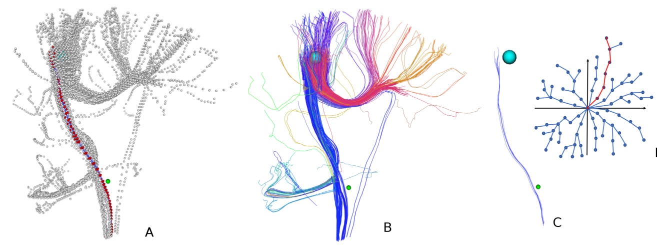

Fig. 1. (A-C) Cyan: centers of start and goal regions . A) Gray: nodes (states) of expanding tree. Red: high rewarded nodes B) All candidate paths of the generated tree. C) Correct paths found., D) actual tree in memory. The root of the tree is at origin (start region). Notice that our algorithm can figure out the correct bundle and nullify the other possible bundles.

3. RESULTS/CONCLUSION

To generate Fig. 1 we used the simulated human brain phantom of ISMRM 2015 tractography challenge [1] (see Fig. 1) to generate reconstruction directions. The design of the experiment is to test how good the system performs on finding streamlines that connect two different parts of the brain that are separated by a crossing region. The method is aiming to find a bundle connects a region close to the MCP, and a higher part of CST. The main input of our method was the reconstruction directions and centers and radii of the spherical ROIs and standard parameters such as the tracking step size.

Our proposed method has multiple advantages. First, the tree structure allows to explore different pathways and remember them. Since exploration paths of differing trials might overlap, the paths repeated on the same tree branch allow the tracker to make quick decisions once high reward states are encountered. Second, our method can be used to adaptively learn the space of bundles and discover the best bundle to reach a specific goal region. Finally, we are working on quantitatively showing the benefits or our approach and investigate the problem of full brain tractography using RL.

4. REFERENCES

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