Deep learning for Tractography

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Abstract – Tractography is one of the most valuable tools for neurosurgeons in preoperative planning since it allows the visualization of both white matter structures and the fibers' distribution in a patient's brain. The best-known classical techniques are either deterministic or probabilistic in providing fiber orientations in voxel resolution. With advances in machine learning, particularly deep learning, a series of elements and new ways of obtaining the fiber structures have been introduced, making tractography a promising, handy, and reliable tool for doctors in their daily diagnostic process. A typical consistent tractography pipeline comprises two stages: diffusion directionality modeling and diffusion-oriented tracking. This paper reviews deep learning-based estimations of local fiber orientations representable by either diffusion tensors or diffusion orientation distribution functions.

Keywords – Tractography, diffusion tensor imaging, fiber orientation distribution functions

1. Introduction

Neural fibers are responsible for highly complex brain connections. Diffusion Magnetic Resonance Images have been used in clinical and research applications to infer white matter structures and brain fiber interconnections, far beyond the resolutions of current images [1] [2]. The process is called tractography. Magnetic resonance imaging has also seen the development of artificial intelligence algorithms. More recently, deep learning-based techniques have been perfecting the levels of reliable neural pathways for making diagnoses and providing a new perspective and interpretation of the information and the results obtained [3]. Algorithms based on deep learning are data driven, so the selection of datasets, input data, pre-processing stages and the associated labels for training imply the elaboration of a training paradigm that guarantees the robustness of the model developed. Despite the progress made so far, there is still a long way to walk to predict tracking directions and stopping within diffusion magnetic resonance imaging because of the complexity of neural pathways [12].

2. Proposal

As deep learning techniques depend on the input data and the manipulation and pre-processing of these data, we proposed a bibliographic survey of the latest deep learning based estimations of fiber orientations algorithms, emphasizing the training datasets capable of deriving the mapping rules from the raw diffusion data to the neural pathways and the applied deep learning algorithms for conducting such derivations.

Diffusion-Weighted magnetic resonance Imaging (DWI) and High Angular Resolution Diffusion Imaging (HARDI) are the most known techniques for sampling the raw diffusion signals of water molecules within a voxel of brain tissue. Most applied ways to synthesize from these raw datasets diffusion directionality in the brain are Diffusion Tensor Imaging (DTI) and Orientation Distribution Function (ODF). From the estimated local diffusion directionality and start seed points, plausible white matter streamlines are expected to be tracked. Although we are looking for a learning algorithm that can derive mapping rules between DWI scans and neural fibers directly from DWI scans and reference streamlines, we chose to first deal with the problem in two stages like Benou and Raviv [11].

There are four major groups of deep learning algorithms: (1) supervised (Convolutional Neural Networks, Long Short Term Memory Networks, Recurrent Neural Networks), (2) semi-supervised (Generative Adversarial Networks), (3) unsupervised (Autoencoders-Autodecoders, Support Vector Machine), and (4) reinforcement (Deep Reinforcement Learning).

2.1 Article Review

In this section, we briefly describe the articles analyzed so far, highlighting the training data used and the deep learning algorithms applied for estimating the diffusion orientations in each brain voxel.

DeepDTI [4] is an algorithm that minimizes the data requirements for its operation. It uses as input an image with b=0 (non-diffusion weighted scan) and 6 DWIs together with the synthesized DTI and T1 and T2-weighted volumes from the WU-Minn Human

Connectome Project (HCP) databases. Data from 70 unrelated subjects were used, with 40 subjects for training, 10 for validation, and 20 for evaluation or testing. The learning algorithm is a deep convolutional network or CNN with 10 layers of 3 dimensions each. The output of this CNN also corresponds to a high-quality volume with b = 0 and 6 volumes of DWIs optimized by the diffusion encoded directions. The authors quantify the performance of the learning algorithm using the quality of the output images, DTI metrics, DTI-based tractography of the reconstruction, and analysis of specific tracts.

In the same direction, SuperDTI [5] is a method also based on CNN, aiming to take advantage of the elements of DTI-based methods. The data are from the databases of the international HCP, consisting of DWIs of 50 subjects divided into 40 for training and validation and 10 for tests. Although the authors also use non-diffusion-weighted and 6 DWI volume, SuperDTI differs from DeepDTI in training CNN parameters. They are trained separately by the FA and MD maps and the eigenvectors, pairwisely. This method eliminates the noise-sensitive tensor fitting process and has quantification errors close to 5% in the regions of interest that contain target white matter and fibers.

Karimi and Gholipour [6] also estimated a diffusion tensor image using six diffusion-weighted scans. They further proposed exploiting the relationships between diffusion signals and tensors in neighboring voxels to improve the tensor estimation accuracy. They applied two-stage transformer neural networks as a learning algorithm. The first estimates the diffusion tensors according to the diffusion signals in a neighborhood of voxels The second refines the estimation of the tensors by learning the relationships between the diffusion signals and the tensors estimated by the first network. They evaluated the proposed method with HCP, scans from the Pediatric Imaging, Neurocognition, and Genetics (PING) dataset, and Vein of Galen Malformation (VOGM) scans.

The diffusion orientation distribution functions head another way to determine the fiber spatial orientations. As they require higher angular resolution diffusion signals, it has driven work related to training algorithms for increasing angular resolution while keeping acquisition time low. Jha, R. R. et al. proposed a machine based on generative adversarial networks (GAN) [7] to obtain more gradient directions for under-sampled DWI volumes with reduced number of directions in q-space.

In [8], Jha, R. R. et al. designed a GAN-based model for synthesizing multi-shell multi-tissue fiber orientation distribution function from the spherical harmonic coefficients of a single-shell HARDI volume at a b-value of 1000. The HARDI signals are transformed into the spherical harmonic coefficients to train the neural network. The performance of the learning capability was evaluated with the HARDI multi-shell dataset from the HCP: 100 randomly selected subjects having volumes acquired with different gradients: b = 0, b = 1000, b = 2000, b = 3000.

On the one hand, the fiber orientation distribution function is better estimated from high angular resolution diffusion imaging. On the other hand, signal acquisition is much more time-consuming. Rui Zeng et al. [9] devised a 3D convolutional neural network to enhance the angular resolution of low-quality single-shell low angular resolution diffusion image (LARDI) data, making them equivalent to those derived from high-quality multi-shell HARDI acquisition. The machine also learns to remove false fibers and recover some fibers present in the original volume, thus allowing a more reliable tract reconstruction in practical clinical situations. The authors randomly selected 110 subjects from HCP, 50 for training, 50 for validation, and 10 for testing.

Lyon, M et al. [10] also investigated a way to overcome a long time in scanning diffusion signals if high angular resolution. They proposed a recurrent CNN autoencoder architecture to infer higher angular resolution diffusion signals without spherical harmonic coefficients. A 3D convolutional long short term memory (ConvLSTM) cell is applied to model the relationship of q-space cells. The authors used HCP datasets for training and evaluating the performance of the proposed model by measuring the deviation of estimated diffusion signals from the ground truth across multiple diffusion directions.

2.2 Training Datasets and Deep Learning Algorithms for Diffusion Orientation Estimation

Table 1 summarizes the learning algorithms used in reviewed articles and the type of data used for training. Supervised learning is the most used, followed by the semi-supervised and one unsupervised learning.

None of the proposals use the raw data directly from the diffusion signals (see Table 1). Instead, the authors preprocessed the data to make them fittable to the learning architecture. Among the papers studied, the combination of DTI model and deep convolutional neural networks seems the one that presents fewer pre-processing stages.

Method	Deep learning algorithm	Input Data	Output Data
DeepDTI	Supervised	T1-weighted T2-weighted + 1 DWI (b = 0) + 6 weighted DWIS	High quality (b = 0) DWI and 6 weighted DWIs
SuperDTI	Supervised	1 DWI (b = 0) + 6 weighted DWIS	Maps(DWIs – FA, DWIs – MD and DWIs – eigenvectors)
Karimi, D Gholipour, A	Semi-supervised	Volumetric 3D Image with 6 Channels (1 channel = 1 of 6 Normalized DWI)	Volumetric 3D Image with 6 Channels (1 channel = 1 of 6 tensor elements)
Jha, . R. R. et.al.	Semi-supervised	Input DWI slice I and Ground truth slice G	Full sample HARDI close to G
Jha, R. R et. al. (VRfRNet)	Supervised	Spherical Harmonics Coefficients (Applied Q-ball imaging on 1K HARDI data)	Predicted Multi-Shell Multi-Tissue fODF
Zeng, R et. al	Supervised	Single-Shell LARDI-FOD image	Super-resolved FOD image
Lyon, M et. al.	Unsupervised	3D dMRI patches + corresponding b-vectors	3D dMRI patches along the given diffusion direction

Table 1. Summary of learning algorithms and data type used.

3. Discussions

All the works analyzed implemented a methodology to obtain the fiber reconstruction with the best possible performance using deep learning and the facilities this technology provides. In general, the data used in each algorithm are from healthy subjects, and the results are compared with the known ground truth, lacking extensive tests in DWI volumes for patients with anatomical malformation. .

As machines learn with data from healthy people, we expect their performance with dMRI of non-healthy people to be inferior to that obtained with healthy people. It would be interesting to train these machines with data of non-healthy people and fine-tuning the training parameters to try to make them appropriate for clinical reality, gain insight into the problems, and look for novel solutions.

The datasets of the Human Connectome Project are used in all the works studied. In some cases, the authors specify the dataset used within the Human Connectome Project: in SuperDTI the HCP Young Adult dataset, in DeepDTI the Human Connectome Project (HCP) WU-Minn-Ox Consortium, Jha, R.R. et al. used the multi-shell HARDI from the WU-Minn Human Connectome Project (HCP) dataset.

The input data for each model varies depending on the type of application to be used, although in general the pre-processing stage largely determines the dimensions and the type of data to be used and introduced into the deep neural networks as inputs. The models based on diffusion tensors require fewer data pre-processing steps than the ones based on orientation distribution functions. Nevertheless, diffusion orientation distribution functions are much more information concerning neural pathways.

4. Conclusions

Deep learning techniques are promising for developing the estimation of local fiber orientation. However, the correct selection of the data to obtain the desired model with good performance is still challenging due to the difficulty involved in making a good selection. In addition, both the choice of the data and its pre-processing stages will affect the degree of complexity of the model developed, an element that affects the further practical implementation of the model obtained. This review improved our understanding of the potential challenges in elaborating a learning algorithm that maps the DWI scans in diffusion direction models (DTI or ODF), their training, validation, and testing. To achieve our goal, we must study alternatives for fiber tracking and analyze a better paradigm to map DWI in tracts. Directly from DWI scans to tractography or in two steps?

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