DT-MRI White Matter Fiber Tractography with Global Constraints

An Unsupervised Learning Approach

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Abstract—**Brain white matter fiber tracking imaging using diffusion tensor magnetic resonance imaging (DT-MRI) traces brain white matter fiber bundle and reconstruct the structures of the fibers according to the diffusion of water molecular in the white matter. In this paper, a novel fiber tracking technique based on well established Unsupervised Learning algorithms was proposed. For a pair of regions of interest (ROIs), a random fiber pathway that connect both ROIs are generated initially. This pathway is evaluated for fitness to the diffusion tensor field and fiber geometric with global constraints. Then another random fiber pathway was generated and compared with the former one. Training was done according to the fitness between the two fiber and weights was renewed to generate new fiber. These processes are iterated until convergence to get a deterministic tracking result and three dimensional white matter fiber structure can get from the multiple results. This method was applied to a synthetic dataset and two sets of in vivo DTI data acquired from different healthy human volunteers. The experiments demonstrate that the fiber tracking algorithm we proposed can reconstruct white matter fiber trajectories faithfully for both synthetic and in vivo DTI data and is insusceptible to image noise and other local artifacts.**

Keywords- Diffusion tensor magnetic resonance imaging, Brain white matter fiber tracking, Unsupervised learning

I. Introduction

Diffusion tensor imaging (DTI) based fiber tractography has become a primary tool for non-invasive exploration of white matter structures and reconstruction of neuronal pathways in the human brain [1]. To date a variety of fiber tracking algorithms have been proposed to infer the connection in the human brain[2, 3, 4, 5], and the basic principle of which is integrating local fiber directions from pre-defined seed point(s) sequentially to generate fiber connection pathways. These methods can be broadly divided into two categories: deterministic fiber tractography and probabilistic fiber tractography. The former one defined a single route between each single voxel, and the latter one repeatedly generated tracking curves to determine the degree of connectivity of a voxel to the seed points. The local uncertainty of fiber orientation at each voxel in the tracking pathway was demonstrated in probability density functions (PDFs) which is defined as the frequency with which pathways pass through the voxel, normalized for the total number of tracking.

A common drawback of this kind of streamline-like tracking methods, either deterministic or probabilistic, is the cumulative errors arising from random image noise and/or partial volume averaging (PVA) along the tracking path [6], even with certain regularizations on the basis of geometric or other constraints. As the result, probability connection maps derived in such methods demonstrate a decrease in the connection probability and spread divergingly as the increase of distance from the start point. On the other hand, as the direction information which stream-like tracking methods follows only represent the information derived in the local area, the tracking results in these method is not a optimal solution of entire fiber pathways. Therefore, the tracking results between two regions of interests (ROI) are unsymmetrical when tracking between them from different ROI as the local information along the tracking pathway from different ROI is unsymmetrical. These disadvantages above make the tracking result difficult for quantitative analysis and application.

In this work, a novel fiber tracking technique based on well established unsupervised learning algorithms was proposed [7]. It allows global constraints to be elegantly imposed on the fiber pathways, and hence possesses superb immunity to local imaging artifacts. Furthermore, it provides solutions for fiber connection pathways between two designated regions of interest; this offers a great potential of applying it to studies of structure-function relations in the human brain, in which the structural connectivity between two functionally related regions is often sought.

II. Method

A white matter fiber path can be demonstrated as a sequence of points in the image space and the fiber tractograthpy can be described as line propagation with an integration scheme:

$$s_{i+1} = s_i + \alpha_i \varepsilon_i \qquad (1)$$

Where s_i is a position vector at discrete step I, α is the step size, and ε_i is a propagation vector.

As the step size α is usually set to be a constant, the dynamic of fiber pathway is only determined by the propagation vector ε_i. Commonly, the major eigenvector of the diffusion tensor constrained with geometric or other factors is used as the propagation vector. However, this kind of estimation just considered the uncertainty due to the inherent noise and PVA in the current step, any bias of estimation will lead to wrong tracking results, and the cumulative errors aroused along the tracking path from random image noise and/or PVA. To reliably track fiber pathways and minimize the cumulative errors, an unsupervised learning based white matter tractography which is constrained by global diffusion information and geometric smoothness on the fiber pathway was proposed. In the sections below, the network configuration was first introduced and followed by implementation details of unsupervised learning fiber tracking.

A. Network Configuration

To obtain the network dynamics, we derive the network updates to optimize the objective cost function over a time scale. The activation and phase variables are simply interpreted as oscillating units described by an amplitude and a phase. The phase for a given unit is derived from an ongoing oscillation whose natural period is fixed for that unit. The network dynamics determine how the initial amplitudes and phases of the units evolve over time.

The network is designed as follows.

- A bottom layer receives inputs from coefficients of the randomly generated fiber. The amplitudes output of these units is the input coefficients, whereas the phase is a function of their natural frequency.
- A top layer consists of dynamical units that have duplex connections with the bottom layer. For these units, the amplitude of output is the coefficients sampled from the two layers and the phase is the same with bottom layer.

The network structure is designed in figure 1:

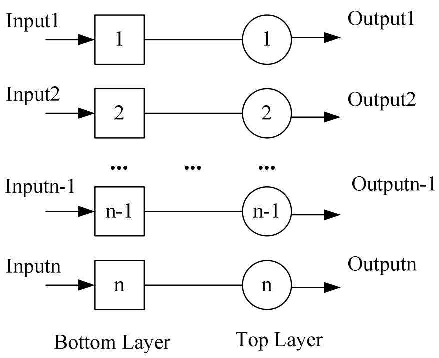

Figure 1. Structure of the network

B. Unsupervised Learning Fiber Tractography

Unsupervised learning algorithms are approximate solutions to optimization problems. Briefly, for a pair of regions of interest (ROIs), two random fiber pathways that connect both ROIs are generated. One of them is applied to top layer as output and another one is applied to the bottom layer as input. These two pathways are evaluated for fitness to the diffusion tensor field and fiber geometric under global constraint. Training was performed as sampling the two layers according to the objective cost function and the top layer are renewed with the sampling results. Then a new randomly generated curve is applied to the bottom layer for the next iteration. These processes are iterated until convergence. Below is the outline of the implementation procedure for one iteration of the algorithm:

1) Initialization: Fiber pathways are space curves (*f*) that can be expressed in Cartesian system as Fourier series, i.e.:

$$f^c(t) = \sum_{n=1}^{N} [a^c_n \cos(nt) + b^c_n \sin(nt)] \tag{2}$$

where c denotes the *x, y, or z* direction in the Cartesian system, n is the order of Fourier series, a_n and b_n are coefficients of the cosine and sine components respectively, and N is the maximum order of Fourier series for approximation with reasonable accuracy. In this work, the maximum order of 10 are generated initially by randomly assigning values to the coefficients a_n and b_n.

2) Training: Each curve is evaluated for fitness to the solution according the cost function below:

$$Cf = \alpha \sum_t \arccos(\tilde{v}_t \cdot \tilde{v}_{t-1}) + \beta \sum_t \arccos(\tilde{v}_t \cdot \tilde{e}_t) \tag{3}$$

where $\tilde{v}_t$ is a unit vector that denotes the tangential direction at the t^{th} point of the curve, and $\tilde{e}_t$ is the major eigenvector of the local diffusion tensor. The first term in the above cost function imposes a smoothness constraint on the fiber pathway, and the second term encourages consistency between the fiber and tensor dominant directions; the relative weights of these two terms are regulated by the parameter α and β.

Top layer is renewed with the coefficients selected from the two fibers in importance sampling scheme gives preferences to fibers with lower values of the cost function. Because each fiber is determined by $2N$ coefficients, the importance sampling scheme mentioned above should be done $2N$ times to get $2N$ coefficients for the corresponding position.

3) Behavior After Training: After training, a new top layer which represents a new fiber curve is get. If it satisfies the terminal conditon, this fiber will be demonstrated as the final tracking path. Otherwise, a new curve is generated randomly to renew the bottom layer for the next iteration. Because there is no prior information for the terminal condition, we define the terminal condition as: in the last k iterations, there are none of the objective cost function of the bottom layer is better than the objective cost function of the top layer, the k is the iteration times.

The final fiber curve get from the unsupervised learning algorithm above is only a single curve of the fiber bundle and can be treat as the deterministic fiber tracking. The three dimensional fiber bundle can be get from multiplying results of applications in this algorithm.

III. Tracking Experiments and Discussion

To evaluate comprehensively the performance of the fiber tracking technique proposed, five synthetic datasets with different geometric complexity were designed. In addition, four sets of *in vivo* DTI data were acquired from different healthy human volunteers.

A. Unsupervised Learning Fiber Tracking with Synthetic Datasets

We commence by evaluating the performance of the algorithm on the synthetic tensor field. The dataset contains 64×64×20 voxels, and the diffusion weighting was simulated along 32 non-collinear directions with b value of 1000 s/mm^2. The diffusion parameters were similar to those in physiological conditions, and the diffusion weighted data were corrupted with zero mean Gaussian noise at a standard deviation of 0.05. The tracking results together with tracking accuracy and precision analysis is demonstrated in figure 2.

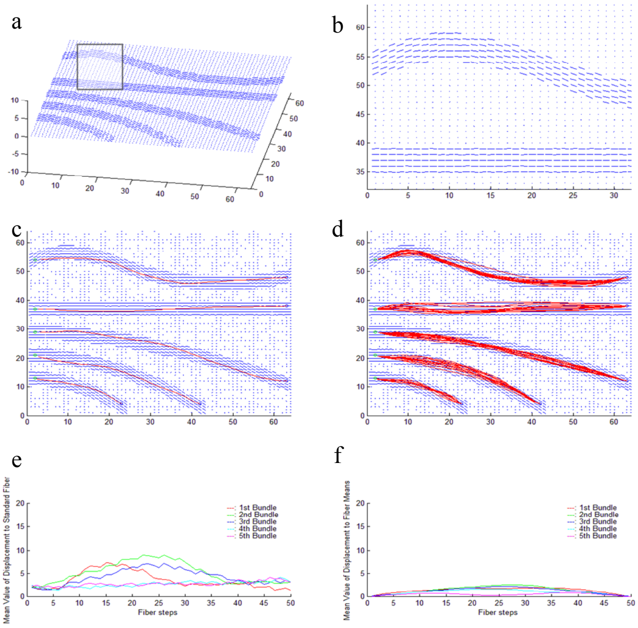

Figure 2. Fibers tracked from synthetic DTI data and their corresponding analysis

Fig.2a is the synthetic ground truth tensor field containing five different fiber bundles with different geometric complexities. The first bundle has two curves and is the most complexity and the follow ones have increasing curvatures. Fig.2b shows a zoomed region of Fig.2a to better visualize the details of the synthetic fibers and the principle diffusion directions of the voxels is alone the stick. Fig.2c is the one time tracking result with unsupervised learning tracking algorithm and it matches the fiber bundles well in all five bundles with different geometric complexities. It means that our algorithm is effective in situations of different geometric complexities. Fig.2d is the 30 times tracking results with our algorithm. The single result is a kind of deterministic tracking result and the multiplying results can demonstrate the whole fiber bundle in three dimensions. It also can be seen that the multiplying tracking curves converge to the fiber pathways very well and demonstrates the robustness of our algorithm with multiply applications. Fig.2e illustrates error distance between a sample point on the ground truth path and the mean of corresponding points of all the tracked paths. It can be seen that the tracking paths is along and converge to the standard path. Fig.2f is the average displacement between the mean of all fibers and individual fiber. It demonstrates that multiply tracking results are converge together and the algorithm is robust to multiply applications.

B. Unsupervised Learing Fiber Tracking with in vivo Human DTI Data

To assess the performance of the Genetrack on *in vivo* data, four sets of DWI data was acquired from a healthy human volunteer on a 3-T GE Signa MR scanner using a single shot, echo-planar pulsed gradient spin-echo imaging sequence. Diffusion weighting was performed along 32 noncollinear directions with b value of 1000 s/mm^2. Timing parameters were TR of 9000 ms and TE of 88.5 ms. The imaging field of view was 240×240 mm^2, 64 contiguous, 2-mm-thick slices with a matrix size of 128×128 were acquired and subsequently interpolated into a matrix size of 128×128, yielding an in-plane pixel size of 0.94×0.94 mm^2. A total of 37 repeated scans were obtained, and images showing motion and other artifacts were discarded. This high SNR (>100) DWI dataset was used for tensor calculation. Diffusion tensor elements were fitted using a weighted least square approach [1], from which FA maps were computed. T1-weighted images were acquired as well during the same session for generation of brain mask images. Prior to the study, the subject gave informed consent for the study protocol that was approved bythe local ethics committee.

As it is not possible to measure quantitatively the accuracy of fiber tracking on *in vivo* data due to the lack of a ‘‘gold standard’’, performance evaluations and method comparisons were based on qualitative judgment of fiber tracts reconstructed. These ROIs were defined using the WFU PickAtlas tool in SPM2 [8] or determined using functional MRI signals [9]. The tracking results are in the figure 3.

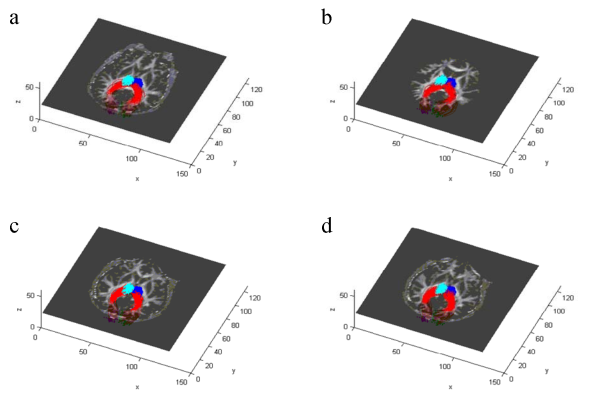

Figure 3. Fibers tracked from *in vivo* DTI data

Fig.3a-d are tracking results for *in vivo* data. These pathways are consistent across the four subjects and tracked between the left/right thalamus and left/right Brodmann's area (BA) 17 in the occipital lobe. The red curves are tracking pathways and the other color points are the ROIs. All the four figures show that the fiber bundles connecting thalamus and Brodmann's area agree the known neuroanatomy well.

IV. CONCLUSION

In this paper, a new method of DT-MRI white matter fiber tractography is presented. Random fiber curves are constrained of global diffusion tensor field and fiber geometric and optimized with unsupervised learning iteratively. After this procedure, the random fiber is reconstructed to demonstrate the three dimensional fiber bundle. Base on the experimental evaluations, the proposed algorithm has the following advantages: first, unlike the previous methods which track fiber under the local information, our algorithm incorporates a global constraint, thus making it insusceptible to image noise and other local artifacts. Second, the tracking result of our algorithm is independent of the tracking direction between two designed ROIs and greatly benefits quantitative analysis and clinic application.

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