Connectivity Measurement using Bayesian Importance Sampling and Re-sampling for Diffusion Tensor Fiber Tracking

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Introduction

The method of probabilistic streamline and other related methods [1-5] have emerged as effective methods for taking into account noise and partial volume effects. These methods have the potential of tracking branching fibers, intersecting fibers, and fibers at gray-white matter boundaries. In these methods, an orientation distribution function (ODF) is calculated for the fiber direction and then Monte Carlo techniques are used for generating fibers. The probability of connection between two regions of interest is then obtained by the ratio of the number of fibers passing through the region of interest and the total number of repetitions.

The probabilistic streamline methods based on standard Monte Carlo techniques are computationally intensive with large demands on memory. We propose an integrated Bayesian sampling and re-sampling techniques to concentrate Monte Carlo tracking on the most likely fiber orientations using both local and neighborhood information. A deterministic re-sampling method is further applied to resample the posterior orientation distribution. This consists of duplicating the orientations with high probability, and removing orientations with low probability. A comparison with standard Monte Carlo methods shows an order of magnitude reduced computation time for connectivity measurement while maintaining similar spatial patterns of high probability fiber bundles.

Theory

In this study we represent the ODF ($P(\theta,\phi,\boldsymbol{r})$) at each voxel $\boldsymbol{r}$ by a discrete approximation which consists of many realizations from the ODF, as is done in the field of Monte Carlo filtering. The posterior ODF at $\boldsymbol{r}$ is proportional to the product of the likelihood function times the priori distribution function (Bayes method). We define the likelihood function to be a function of the local diffusion tensor at $\boldsymbol{r}$, modified by the diffusion tensor of its neighbors in the forward direction [2]. The priori distribution function is a function of the local fiber curvature [1]. The local ODF is calculated by generating a set of uniformly oriented vectors around the major axis of the diffusion tensor at $\boldsymbol{r}$, and multiplying these by an appropriate power (= 3) of the diffusion tensor [3]. Increase in the power order increases the focusing of the sample vectors for anisotropic tensors.

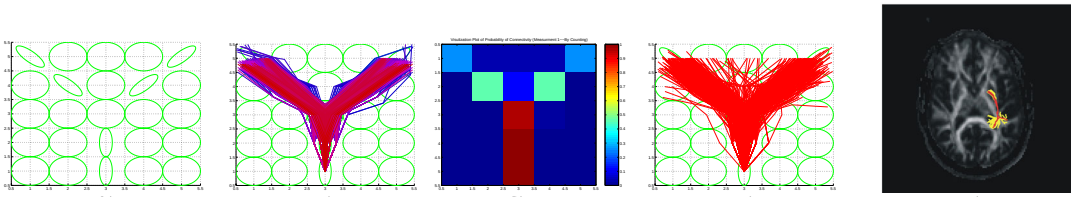
An important improvement we suggest is the re-sampling of the voxel ODF so that the number of realizations is reduced by representing many realizations in more probable directions by fewer realizations with larger weights in the more probable directions. We use the deterministic re-sampling method suggested by Kitagawa [6] for this purpose. These higher weights can be considered to be multiple fibers in these directions. The advantage of re-sampling is that fewer fibers are tracked than the previous methods, leading to faster computation times.

In standard Monte Carlo method if N fibers are tracked for connectivity measurements and there are m steps per fiber, then we have to evaluate tracking information at $N*m$ nodes. In the present method, the number of fibers at each node are variable (because of re-sampling), but on average let us suppose that there are p fibers. Then in m steps we will have evaluated $1 + p + p\text{^}2 + \ldots + p\text{^}(m-1) = (p\text{^}m - 1)/(p - 1)$ nodes and $p\text{^}m$ fibers. This means that in the standard Monte-Carlo method we would have evaluated $(p\text{^}m)*m$ nodes. The ratio of the nodes evaluated in the standard method to our method is approximately $p*m$ for the same total number of fibers. Thus, the computation time saving with the present method increases rapidly with the increase of fiber tracking steps. In practice, the tracking will be even faster than this estimate because re-sampling will have concentrated the distribution in the important directions.

Material and Method

The fiber tracking experiments were done with simulated and in-vivo human brain data. The simulated data sets consisted of three data sets consisting of a) spirals, b) branching fibers and c) intersecting fibers. The performance of fiber tracking was evaluated in presence of noise with standards deviation of (0, 0.05 and 0.1). Human DTI data was obtained on a Siemens 1.5T scanner with a resolution of 2x2x2mm, 128x128 matrix and 64 slices, Tr = 9800ms and Te = 86ms. The diffusion data was taken 12 gradient directions with b = 1000 s/mm2, and NEX =2. The total experiment time was 6 min.

Results



A) B) C) D) E)

One example of simulated data for branching fibers is shown above. In Fig. A we show the base pattern for the branching simulation. In Fig. B, we show 1000 fibers with the highest connectivity, and in Fig. C we show the connectivity map. The connectivity map agrees with the basic intuition of being higher in the beginning and decreasing symmetrically with branching. A comparison with the standard Monte Carlo method (Fig. D), where 1000 multiple fibers were followed individually, generated similar pattern for the fibers but the total tracking and connectivity measurement time was 50 times longer than our method. In Fig. E we show an example of 3D fiber tracking with branching with the data being projected onto a 2D slice. The yellow fibers are 500 fibers with highest probability and red bundle are the first 10 most probable fibers.

Discussion and conclusions

In this study, we have shown that the proposed fiber-tracking and connectivity measurement algorithm can track branching and intersecting fibers similar to other tracking methods based on probabilistic streamlines, while doing it faster. The main reason for this was our ODF re-sampling method which concentrated on important orientations. This method may be useful for measuring the anatomical connectivity information of brain tissues in combination with the measurements of functional connectivity information obtained from fMRI.

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Reference

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