

# Algorithm and SNR Dependence of DTI Fiber Tractography

B. Chen<sup>1,2</sup>, S. Mori<sup>3</sup>, and A. W. Song<sup>2</sup>

<sup>1</sup>Biomedical Engineering Department, Duke University, Durham, NC, United States, <sup>2</sup>Brain Imaging and Analysis Center, Duke University, Durham, NC, United States, <sup>3</sup>Department of Radiology and Radiological Sciences, The Johns Hopkins University School of Medicine, Baltimore, Maryland, United States

## Introduction

Imaging noise will influence the accuracy and stability of final fiber tracts in diffusion tensor imaging. It is often seen that the spatial trajectories of tracked fibers do not share complete spatial resemblance for two DTI scans on the same subject under identical tracking conditions. This reproducibility problem hampers plans for data sharing and comparison between difference DTI studies. To improve the reliability of fiber tracking, many signal averages for higher SNR is one of the most commonly used methods and has been effective in improving the accuracy and consistency. Nevertheless, this comes at the cost of much prolonged imaging time which can be impractical in some human experiments, especially in patients and pediatric populations. In this study, we propose a new tracking procedure based on a continuous field construction and demonstrate its faster fiber tract convergence even with a limited number of averages in comparison to the standard Euler's method.

## Methods

Fifteen DTI datasets of one human subject with identical scan parameters were acquired by the BIRN (Biomedical Informatics Research Network) project at JHU with 24×24×6.5 cm field of view and cubical voxel size. The acquired images were zero-filled from matrix size 96×96×25 to 256×256×25. The rigid body registration was used to co-register the fifteen intra-subject DTI datasets. The diffusion weighting directions were rotated accordingly based on the rotational matrix during registration [1]. Because each DTI dataset had a different diffusion weighting directional scheme after registration, direct signal averaging could not be applied. In this study, we took the averaged b0 images and stacked all diffusion weighted images from the averaging datasets to calculate the diffusion tensor. The diffusion tensors, from  $\mathbf{D}_1$  to  $\mathbf{D}_{15}$  (one average to 15 averages), were decomposed into eigenvalues and eigenvectors ( $\mathbf{V}_1$  to  $\mathbf{V}_{15}$  as the principal eigenvectors of  $\mathbf{D}_1$  to  $\mathbf{D}_{15}$ ).

The fiber tracking started from the same ROI selected in the middle of the frontal corpus callosum. We developed an improved tracking method based on the fourth order Runge-Kutta algorithm (RK) on a continuous eigenvector field with tri-cubic interpolation. Euler's method, which is similar to the FACT algorithm [2], was used to serve as a reference as it is widely accepted in practice. For both methods, the most averaged eigenvector field  $\mathbf{V}_{15}$  was used as a standard for convergence comparisons. The spatial similarity of fibers tracked by each eigenvector field was quantitatively characterized against the fibers tracked using  $\mathbf{V}_{15}$ .

For a quantitative comparison among the fibers with different lengths, a reproducibility parameter was defined as the Hausdorff distance per unit track length.

$$R = H(A, B) / \langle A, B \rangle$$

where  $R$  is the defined parameter of reproducibility,  $H(A, B)$  is the Hausdorff distance between track  $A$  and  $B$ ,  $\langle A, B \rangle$  is the mean length of track  $A$  and  $B$ . The Hausdorff distance used to quantitatively characterize the similarity between two tracks is defined as

$$H(A, B) = \max\{h(A, B), h(B, A)\}$$
$$h(A, B) = \max_{|P_a \in A} \{ \min_{|P_b \in B} \{ \text{dist}(P_a, P_b) \} \}$$

where  $h$  is the one way Hausdorff distance. Two tracts,  $A$  and  $B$ , are 3D curves represented by two sets of points ( $P_a$  and  $P_b$ ).  $\text{dist}(P_a, P_b)$  is the Euclidian distance between  $P_a$  and  $P_b$ . The smaller number of Hausdorff distance represents higher spatial resemblance between two curves. Thus, we can quantitatively evaluate the tracking similarity and reproducibility with  $R$  values.

## Results

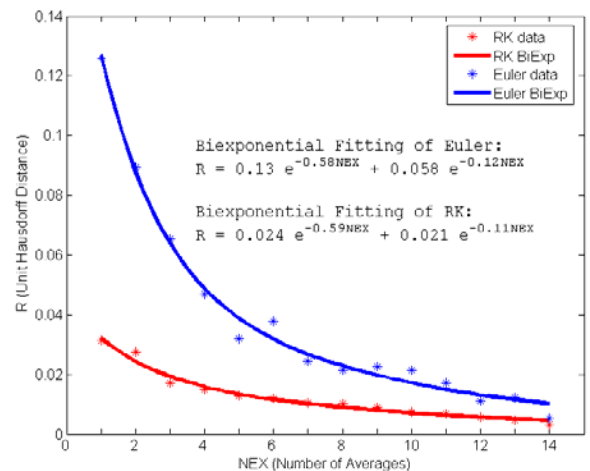
Figure 1 shows the averaged  $R$  values of all fibers tracked using Runge-Kutta method under different averages as compared with Euler's method. As expected, both methods show increased tract similarity with more averages. However, Runge-Kutta method achieves much quicker convergence for the fibers, which can be best fit by a bi-exponential function. The optimal number of signal averaging for the best temporal yield for tract similarity, which is determined by the turning point from the fast to slow exponential decays, is approximately 3 for RK. This delivers similar results as those obtained with 9 or 10 averages with Euler's method.

## Discussions and Conclusions

Tracking algorithms with high order accuracy, such as Runge-Kutta method after tri-cubic interpolation of the eigenvector field, has better performance in tracking stability and convergence compared with the standard method. The resultant high fiber resemblance with limited number of signal averages will be useful in human DTI studies, especially in patients and in pediatric populations.

**Acknowledgment:** Bennett A Landman, Department of Biomedical Engineering, Johns Hopkins University School of Medicine, Baltimore, Maryland. This work was supported by RR 21382.

**References:** 1. Landman BA, Farrell J, Mori S, van Zijl PCM, Prince JL. ISMRM 2006, Abstract# 2987; 2. Mori S, Crain BJ, Chacko VP, van Zijl PCM. Ann Neurol 1999;45:265–269.



**Figure 1:** The track trajectory similarity increases as signal average increases for both methods. The RK method has better performance in comparison to Euler's method under the same averages. It needs less number of averages to generate fiber tracts with high resemblance.