ICA-based Multi-Fiber DWI Tractography in Neurosurgical Planning

Sinchai Tsao*[1,2], Niharika Gajawelli*[1,2], Peter A. Michels[1,2], Darryl Hwang[1,2], Yi Lao[1,2], Fernando Yepes[1], Vidya Rajagopalan[1], Meng Law**[2], and Natasha Lepore**[1,2]

[1] Children's Hospital Los Angeles, Los Angeles, CA , USA,
[2] Department of Radiology and Biomedical Engineering,
University of Southern California, Los Angeles, CA, USA
*,** These authors share equal contribution
gajawell@usc.edu

Abstract. Diffusion Tensor Imaging is a powerful imaging modality that allows us to investigate the underlying white matter fiber structure of the brain. However, it has many limitations, including its inability to resolving fiber crossings. Many multi-fiber techniques attempt to solve this problem, but they often require high power computation as well as High Angular Resolution Diffusion Imaging (HARDI) data [1]. Since diffusion imaging has the potential to contribute to the presurgical planning by clearly delineating white matter anatomy and integrity, it is important to determine methods that solve the crossing-fiber problem in the clinical setting. Here, we explore the use of a recently developed tractography technique that utilizes Independent Component Analysis (ICA)-based multi-fiber orientation estimation. This ICA-based technique leverages neighborhood voxel information for fiber estimation and has been shown to function especially well with clinical data that have small number of gradient directions and b-values, using limited computation power and time [2,3]. We were able to reconstruct estimations of the white matter corticospinal tracts from both of the MICCAI 2013 Challenge neurosurgical cases. Patient 1 demonstrates penetration of the corticospinal tract by the mass, suggesting that complete retraction of the glioblastoma would result in severe distruption of the right CST. Any remaining right CST related function could be lost. Patient 2 shows some displacement of the right CST. When comparing to the contralateral left CST, the right CST seems to be relatively intact. The mass also seems to have displaced a small portion of the right CST. In conclusion, the ICA-based method performed relatively well in both patients, clearly delineating the CSTs relative to their respectives masses. Our method also showed marked improvements when compared with the single-fiber DTI model.

Keywords: MRI, ICA, DTI, Tractography, DWI, Neurosurgery, Multi-Fiber

1 Introduction

Radiological examinations play a crucial role in surgical planning and guidance. Magnetic Resonance Imaging (MRI), in particular, is of considerable use due to the lack of ionizing radiation, and can serve not only for treatment planning but also for evaluating outcomes. In surgical oncology, preoperative radiological examinations not only provide information about the extent of masses as well as indication of the degree of necrosis and edema, but also give a measure of tissue integrity not observable intraoperatively. In particular, preservation of white matter connectivity can severely affect postoperative outcomes in terms of both behavior and function. In this challenge, we attempt to mediate postoperative motor function loss by accurate delineation of the corticospinal tracts using diffusion weighted imaging and tractography.

Diffusion weighted imaging (DWI) is a unique modality in medical imaging which enables us to model the diffusion pattern of water in the brain. The most commonly used DWI method is diffusion tensor imaging (DTI), in which rank 2 tensors or 3 x 3 matrices are computed at each voxel using the diffusion weighted images. The primary eigenvector indicates the primary direction of unrestricted diffusion in a particular voxel and is thought to be aligned with neuronal fiber paths in the brain.

This model of diffusion, however, does not take into account fiber crossings which have been hypothesized to occur in the majority white matter voxels in the brain[4]. Currently, there are many other models using high b-values, and large numbers of gradient directions such as HARDI[1] or diffusion spectrum imaging (ADD REF) data, but these datasets are hard to acquire in a clinical settings due to limitations in acquisition time. Our method attempts to circumvent these issues by estimating multiple fibers in each voxel using clinical data with limited b-values and gradient directions, and utilizing much lower computational resources when compared to methods such as spherical deconvolution (ADD REF).

2 Methods

Table 1: DWI Information

	Patient 1	Patient 2
Number of Gradient Directions	20	20
Image Size ($mm \times mm$)	1.14 x 1.14	1.14 x 1.14
Slice Thickness(mm)	5.2	5.2
b-value (mm/s)	1000	1000
Number of Slices	30	29
Number of Repetitions	4	4

2.1 Data

The 2013 MICCAI DTI Challenge provided participants with DWI datasets from two neurosurgical cases. Patient 1 has a recurrent/residual glioblastoma W.H.O Grade IV. No pathology information was given for Patient 2. Diffusion weighted images were provided in the NRRD format with 20 gradient directions, each with a b-value of 1000 s/mm^2. Patient 1's image had 30 slices and Patient 2 had 29 slices. The acquisition was repeated 4 times with voxel dimensions: 1.14 mm x 1.14 mm x 5.2 mm. Co-registered anatomical images as well as a labeled tumor volume were also provided.

2.2 Pipeline

All data including the DWI data was first converted to a NIFTI file format and checked for obliqueness and consistency in orientation. Next, we computed a mean DWI, using the 4 base volumes provided a mask of the brain with AFNI[5] (THIS SENTENCE IS NOT CLEAR). We then use Independent Component Analysis to recover the directions of individual fibers from a mixture of fibers within a voxel. Display and render of tracts as well as filtering was done using TrackVis[6].

2.3 Independent Component Analysis

Consider the diffusion field of a fiber as the source, and the voxel as a sensor; in this formulation each voxel is considered to be "sensing" signals from multiple sources. The implementation of our multi-fiber "unmixing" paradigm is based on the paper by Singh et al 2010[2]. The attenuated diffusion signal from each of the gradient directions, X_i can be written written as $X_i = S_i/S_0$, where i is each gradient direction, S_i is the diffusion weighted image and S_0 is the non-diffusion weighted scan.

In using ICA, a few assumptions were made: (1) Fibers cross through multiple voxels maintaining their orientation and (2) Fiber signal sources are independent. The latter assumption is made considering the rather large size of voxels (on the order of mm) compared to the order of diffusion of water molecules in axons (on the order of 10um). Unless the diffusion time is extremely long, molecules diffusing around axons of one fiber will not have a significant interaction with those diffusing around axons of another fiber. Therefore similar to the conventional ICA construction, assuming we have k fibers crossing in a small neighborhood of n voxels, we can formulate the fibers as k independent sources, $s_1, \ldots, s_k$ from $x_1, \ldots, x_n$ measurements:

$$x_i = \sum_{j=1}^{k} a_{ij} sj \ \forall i = 1, 2, \ldots, n \tag{1}$$

where a_{ij} is the mixing fraction of j-th source in the i-th voxel.

The aim in ICA is to find a linear transformation of the dependent sensor signal x_i that makes the outputs as independent as possible. In vector-matrix notation: $\mathbf{x} = \mathbf{A}\mathbf{s}$ *or* $\mathbf{s} = \mathbf{A^{-1}}\mathbf{x}$. Each linear combination $y_j = \sum w_{ij} xi$ would be an estimate of a single source if each row of matrix $\mathbf{A^{-1}}$ is w_{ij}. ICA assumes that the sources are non-Gaussian and Singh et al 2010[2] showed that the S_i/S_0 distributions of a single fiber are approximately non-Gaussian. Therefore ICA should correctly assume that the sum of non-Gaussian variables would be increasingly more Gaussian than our original source. From this fact, we postulate that the W_{ij} that maximizes the non-Gaussianity of yi give an accurate estimation of the orientation of our sources. To solve for this linear transformation, we started with a random set of w_{ij}, and used a center voxel surrounded by $n-1$ voxels to maximize the non-gaussianity of y_j with the fastICA algorithm[7], which relies on negentropy to maximize non-gaussianity. After computing the sources using ICA, DTI processing was done to calculate the tensors and estimate the fiber directions.

2.4 Tractography

Whole-brain streamline tractography was performed from the ICA fiber estimations. At each point, the consecutive direction was estimated as the weighted sum of correlated directions from neighborhood voxels. The parameters used were as follows:

Table 2: Tractography Parameters

Type:	Streamline
FA Stopping Threshold:	0.02
MD Stopping Threshold:	4.00
Track Step Length:	0.1 mm
Max Number of Steps:	4000
Maximum Change in Angle:	45°
Number of Neighborhood Voxels used in ICA Estimation:	8

3 Results

Figures 1 and 3 show the results of our ICA-based multi-fiber tractography for Patient 1 and 2, respectively. For comparison, we ran the exact same streamline algorithm but instead used the primary eigenvector orientation from single-fiber DTI as our estimate of fiber orientation in Figures 2 and 4. We rendered the tracts in front of a coronal color FA slice to give a sense of overall orientation in the brain. The tumor volume is rendered as a semi-opaque volume on the right.

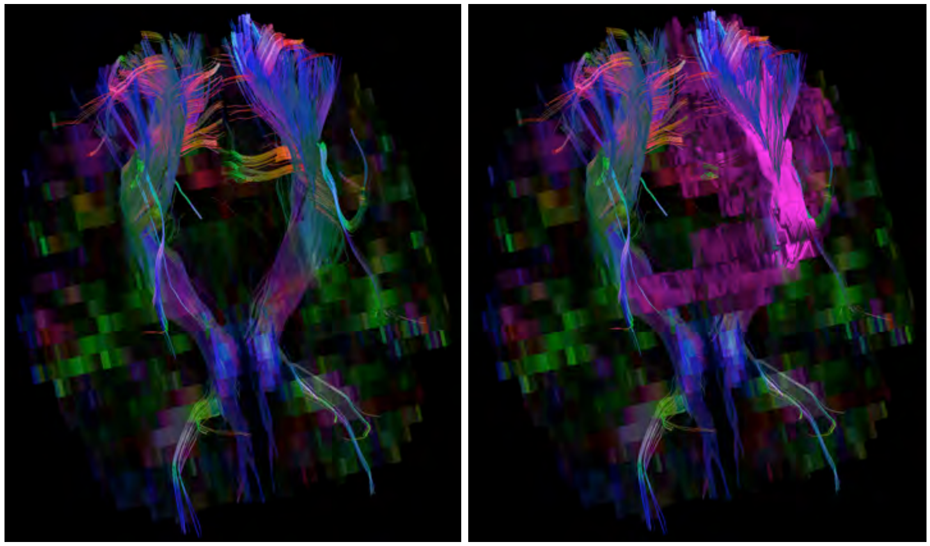

Fig. 1: Patient 1 CSTs using multi-fiber ICA-based tractography with coronal slice showing color FA; without tumor volume (L) and with tumor volume (R).

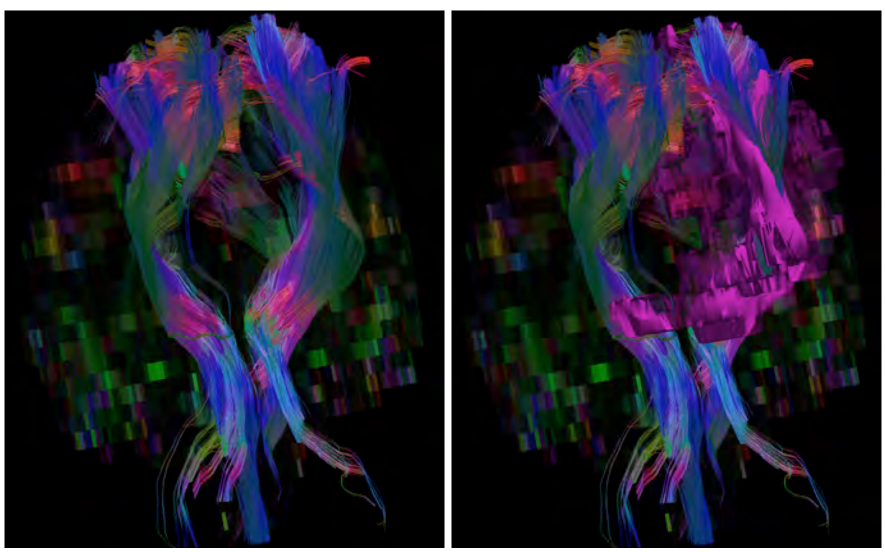

Fig. 2: Patient 1 CSTs using single-fiber DTI tractography with coronal slice showing color FA; without tumor volume (L) and with tumor volume (R)

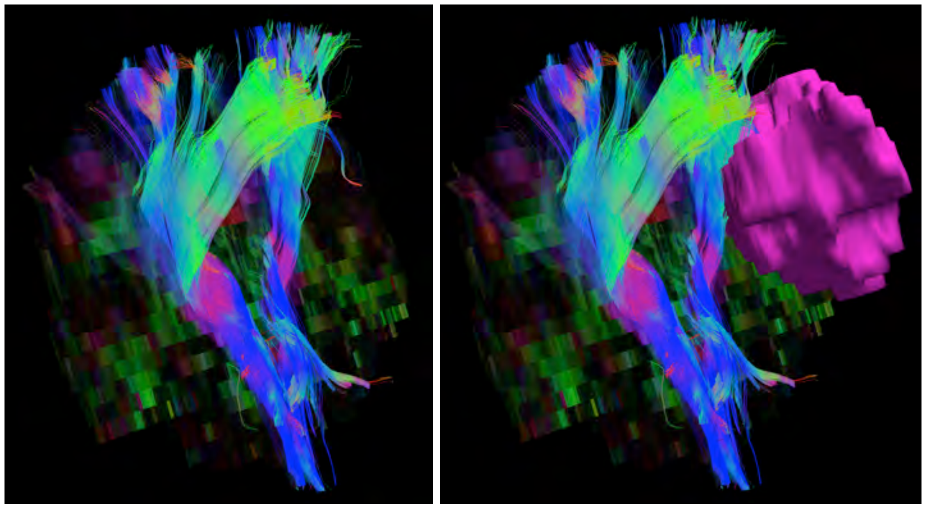

Fig. 3: Patient 2 CSTs using multi-fiber ICA-based tractography with coronal slice showing color FA; without tumor volume (L) and with tumor volume (R)

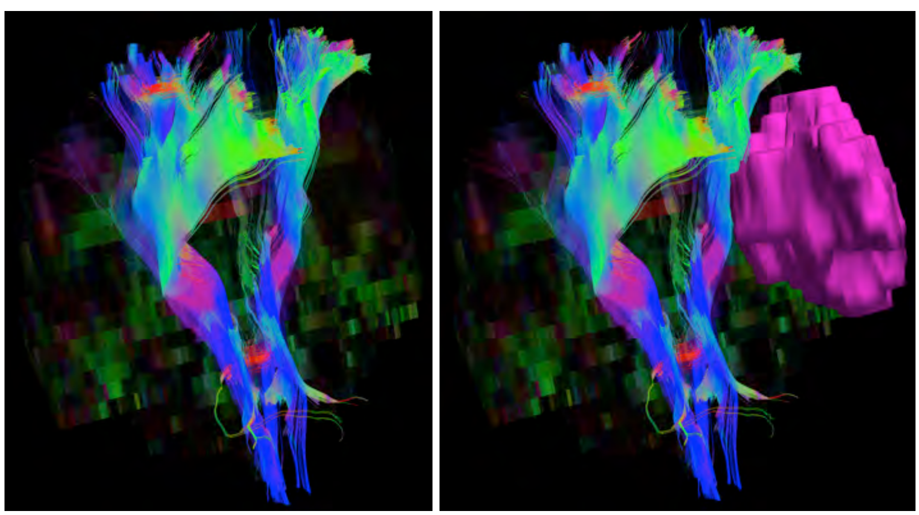

Fig. 4: Patient 2 CSTs using single-fiber DTI tractography with coronal slice showing color FA; without tumor volume (L) and with tumor volume (R)

4 Discussion and Conclusion

This paper demonstrates the performance of ICA-based DWI tractography of the CST in two neurosurgery cases. Patient 1 has a tumor that is positioned central to the CST tract and is more challenging than Patient 2. In the former case, the differences between single-fiber tractography versus multi-fiber ICA-based tractography is more obvious. However, upon closer inspection the differences between single-fiber tractography versus multi-fiber tractography become increasingly stark in the peritumoral regions as well as regions of known crossings near the corpus collosum, cerebral cortex as well as lower down in the brain stem.

The authors believe that the multi-fiber neighborhood technique may have mitigated some of the effects of edema from the tumor. This is possible because the edema component can be seen as a independent source of signal consistent across neighborhood voxels close to the tumor. We also believe that the large 5.2 mm slice thickness may be causing more severe partial volume effects. The non-isometric voxel sizes may also cause directional biases downstream from the tensor estimation and may affect tractography results. From previous work with non-isometric voxels, the authors observed differential performance from the ICA methodology between isometric and non-isometric voxels.

More work needs to be done to determine whether the increased signal-to-noise ratio of the larger slices outweigh the distortion effects it may have on multi-fiber and streamline tractography techniques that rely on neighborhood information. The geometry of the tracts in question may also determine the optimal geometric configuration of voxel sizes and location. In this case, the CST tractography may seem denser simply because of the direction bias in the Ventral-Rostral direction caused by increased slice thickness in the Z-direction and may be mistaken for improved results. This can be seen in the comparison between our single-fiber and multi-fiber methods in patient 2 where the ICA-based methods seems to have decreased fiber density but also less noise at the peritumoral regions as well as the end points of the tracts.

In conclusion, this paper (1) demonstrates application of a computationally thrifty multi-fiber orientation estimation methodology suitable for neurosurgical planning applications, (2) revisits and examines its performance against traditional tractograpy using DTI's primary eigenvector but in a clinical neurosurgical setting and (3) aims to be the first step towards fine tuning both imaging as well as tractographic parameters for eventual vetting of the ICA methodology as a viable multi-fiber tractographic tool for neurosurgical planning.

Acknowledgements The authors would like thank their colleagues Alec CW Wong, PhD and Bryce Wilkins for all their efforts in developing and testing ICA-based tractography. This work would not be possible without their tireless dedication to science. We would also like to dedicate this publication in memory of their late advisor Professor Manbir Singh, PhD who championed the ICA methodology and whose guidance we miss dearly daily.

References

1. Tuch, D.S., Reese, T.G., Wiegell, M.R., Makris, N., Belliveau, J.W., Wedeen, V.J.: High angular resolution diffusion imaging reveals intravoxel white matter fiber heterogeneity. Magnetic Resonance in Medicine **48**(4) (2002) 577–582
2. Singh, M., Wong, C.W.: Independent component analysis-based multifiber streamline tractography of the human brain. Magn Reson Med **64**(6) (Dec 2010) 1676–84
3. Singh, M., Wong, C.W.: Recovery of multiple fibers per voxel by ica in dti tractography. Conf Proc IEEE Eng Med Biol Soc **1** (2006) 735–8
4. Wedeen, V., Wang, R., Schmahmann, J., Benner, T., Tseng, W., Dai, G., Pandya, D., Hagmann, P., D'Arceuil, H., De Crespigny, A.: Diffusion spectrum magnetic resonance imaging (dsi) tractography of crossing fibers. Neuroimage **41**(4) (2008) 1267–1277
5. Cox, R.W., et al.: Afni: software for analysis and visualization of functional magnetic resonance neuroimages. Computers and Biomedical research **29**(3) (1996) 162–173
6. Wang, R., Benner, T., Sorensen, A., Wedeen, V.: Diffusion toolkit: a software package for diffusion imaging data processing and tractography. In: Proc Intl Soc Mag Reson Med. Volume 15. (2007) 3720
7. Hyvärinen, A., Oja, E.: A fast fixed-point algorithm for independent component analysis. Neural computation **9**(7) (1997) 1483–1492