



# MetroTrac: A Metropolis Algorithm for Probabilistic Tractography

Anthony Sherbondy, Michal Ben-Shachar, Robert Dougherty, David Akers, Sandy Napel, Brian Wandell

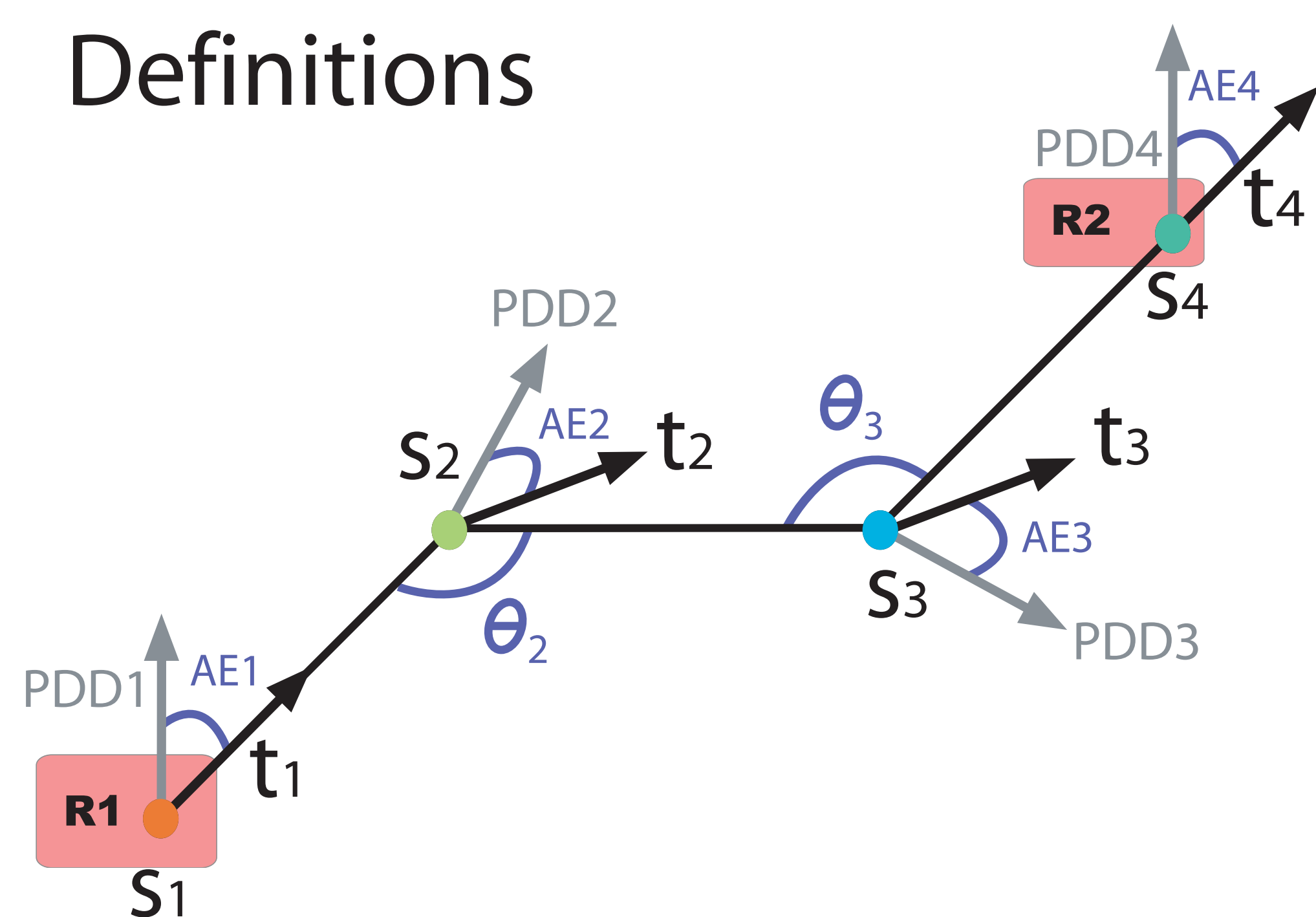
Departments of Electrical Engineering, Psychology, Computer Science and Radiology, Stanford University, CA, USA

## Introduction

Deterministic tractography algorithms, e.g. STT [1], produce reliable estimates of large fiber tracts but do not account for the uncertainty inherent in DW data. Here we present a Bayesian probabilistic tractography framework [2] that incorporates (a) a local diffusion likelihood model [3] and (b) a fundamental fiber regularization parameter found in many deterministic algorithms.

We introduce a Metropolis algorithm (MetroTrac) that correctly samples from this distribution. MetroTrac is efficient at sampling pathways that connect specific regions, even when these regions are separated by major crossing pathways.

## Definitions



$S(R1, R2)$ : Set of all paths that connect  $R1$  and  $R2$

$s = \{s_1, s_2, s_3, \dots, s_n\} \in S(R1, R2)$ : Pathway

$t_i$ : Tangent at node  $s_i$

$D = \{D_1, D_2, D_3, \dots, D_n\}$ : DTI data along  $s$

$PDD_i$ : Principal Direction of Diffusion for  $D_i$

$FA_i$ : Fractional Anisotropy for  $D_i$

$AE_i = \cos^{-1}(t_i^T PDD)$

$\theta_i = \cos^{-1}\left(\frac{(s_j - s_{j-1})^T (s_{j+1} - s_j)}{\|s_j - s_{j-1}\| \|s_{j+1} - s_j\|}\right)$

## Bayesian Pathway Scoring

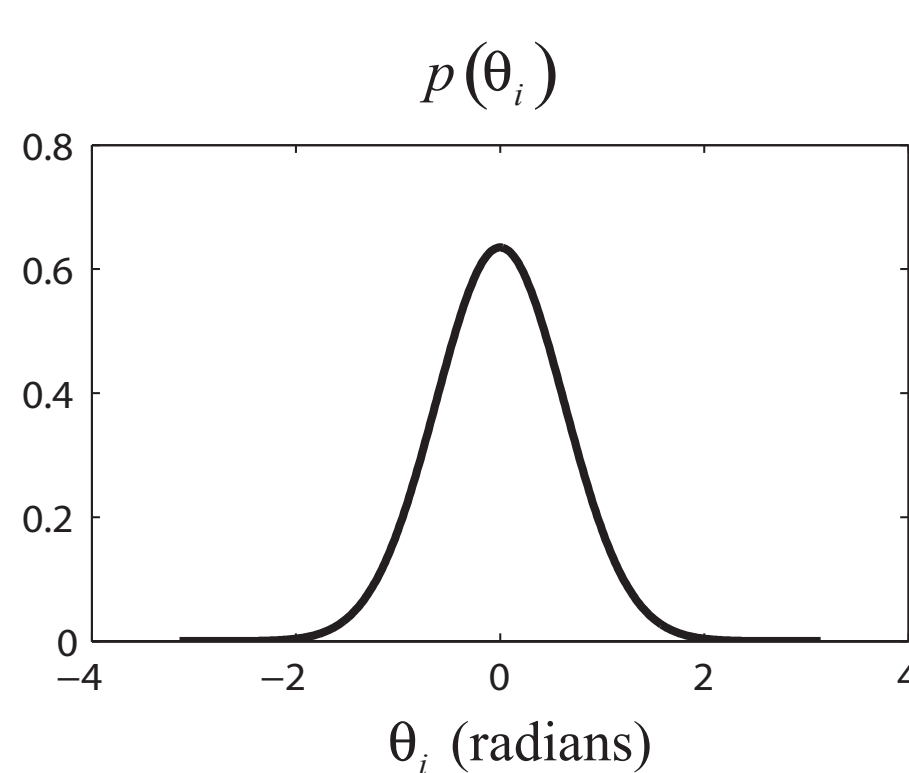
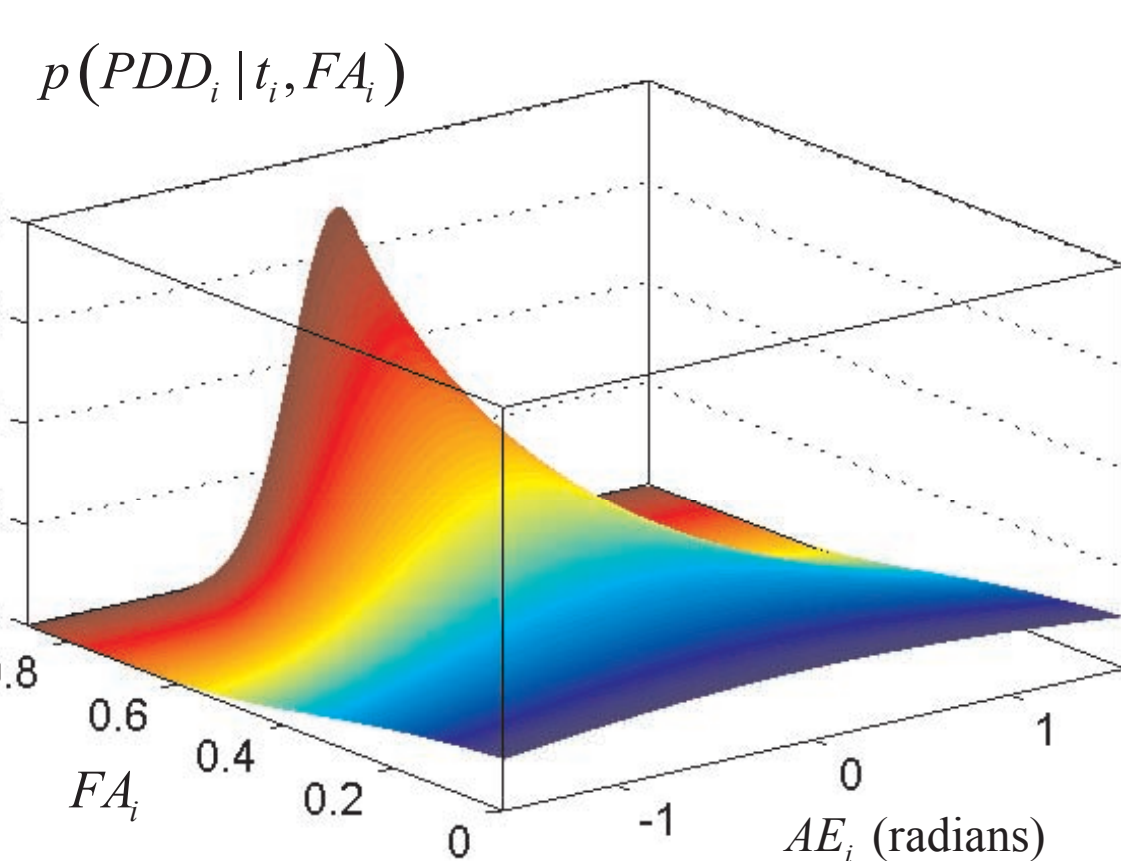
Target Posterior:  $p(s | D) \propto p(D | s)p(s)$

Likelihood (Parker et al. [3]):

$$p(D | s) = \prod_{i=1}^n p(PDD_i | t_i, FA_i)$$

Prior (smoothness):

$$p(s) = \prod_{i=2}^{n-1} p(\theta_i)$$



## Methods

We tested the algorithm in 4 subjects by probing for suspected callosal pathways terminating in human MT+, a visual region on the lateral surface of the occipital lobe.

\* Left MT+ was localized in each subject using fMRI (moving pattern vs. fixation).

\* DTIQuery [6] used for tractography visualization.

\* DTI details (Dougherty et al. [4,5]): 48-54 axial 2mm slices were collected on a 1.5T scanner for b=0 and b=800 using a diffusion-weighted, single-shot spin-echo EPI sequence [TE = 63ms; TR = 6s; bandwidth=110 kHz; partial k-space acquisition; 8-14 repeats; 12 directions (6 non-collinear); voxel size=2x2x2mm].

## MetroTrac Principles

Pathway scores obey properties of **independence** (from data not along path) and **symmetry** (along path):

**Independence**

$$p(s | D, D^c) = p(s | D),$$

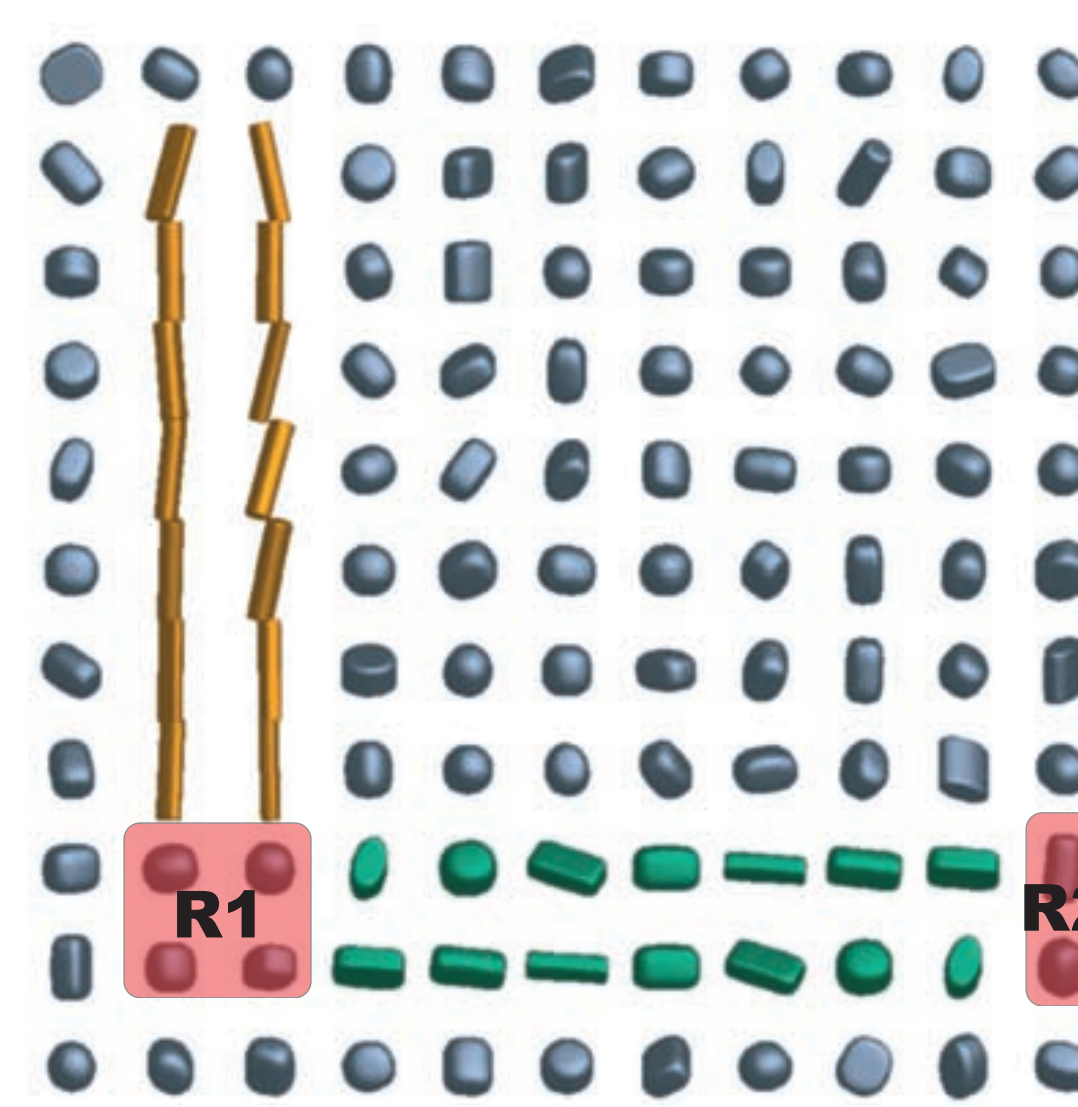
where  $D^c$  is DTI data not along path  $s$ .

**Symmetry**

$$s = \{s_1, s_2, s_3, \dots, s_n\}$$

$$s' = \{s_n, s_{n-1}, s_{n-2}, \dots, s_1\}$$

$$p(s | D) = p(s' | D)$$



## MetroTrac Algorithm

\* It is impossible to score all possible white matter tracts.

\* MetroTrac uses the Metropolis algorithm [7] to discover tracts with the highest scores.

\* Asymptotically, the algorithm is guaranteed to sample paths with a frequency proportional to their score.

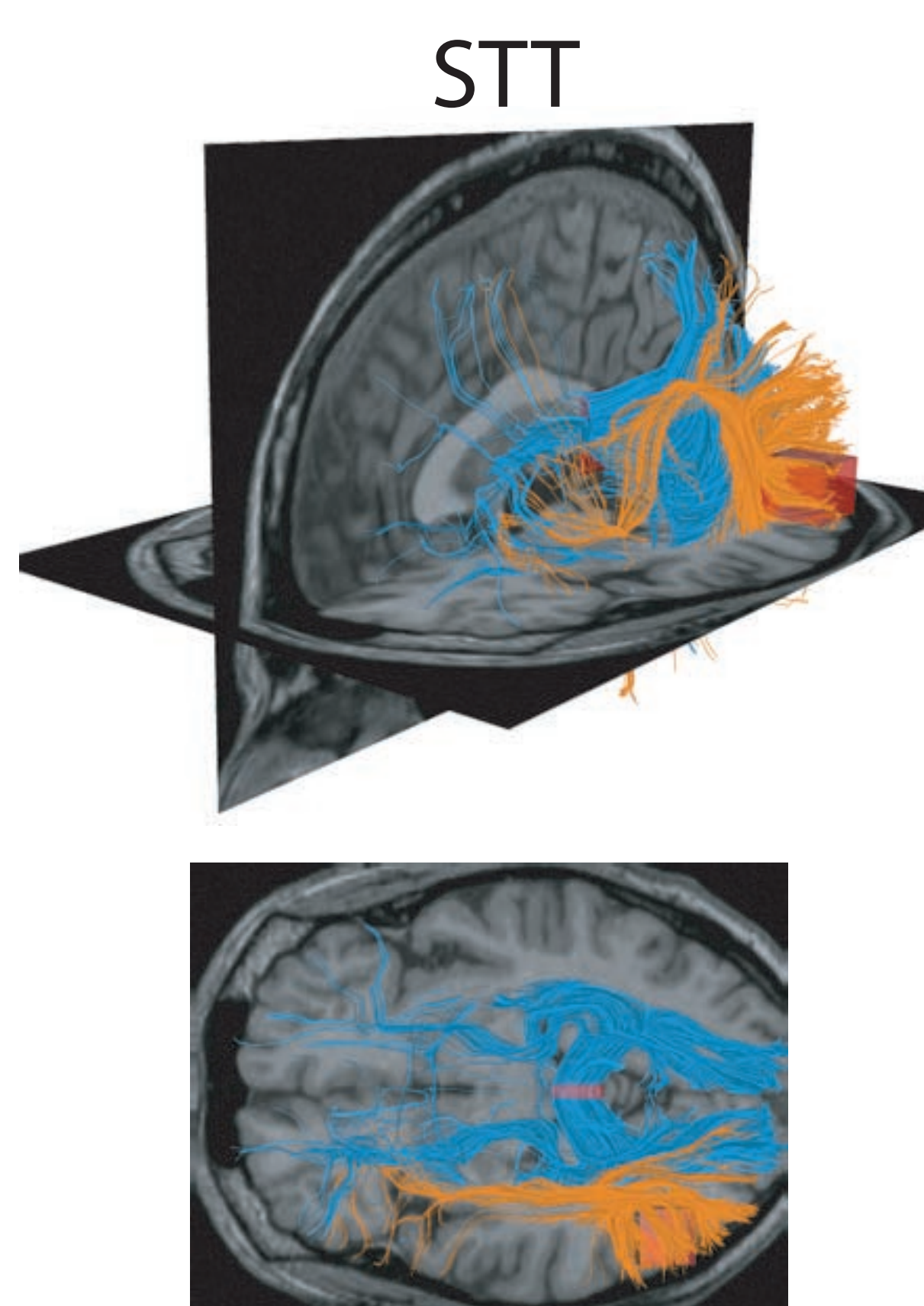
\* The convergence rate depends on how well the software designer chooses path mutations.

## MetroTrac Detects Pathways Invisible to STT

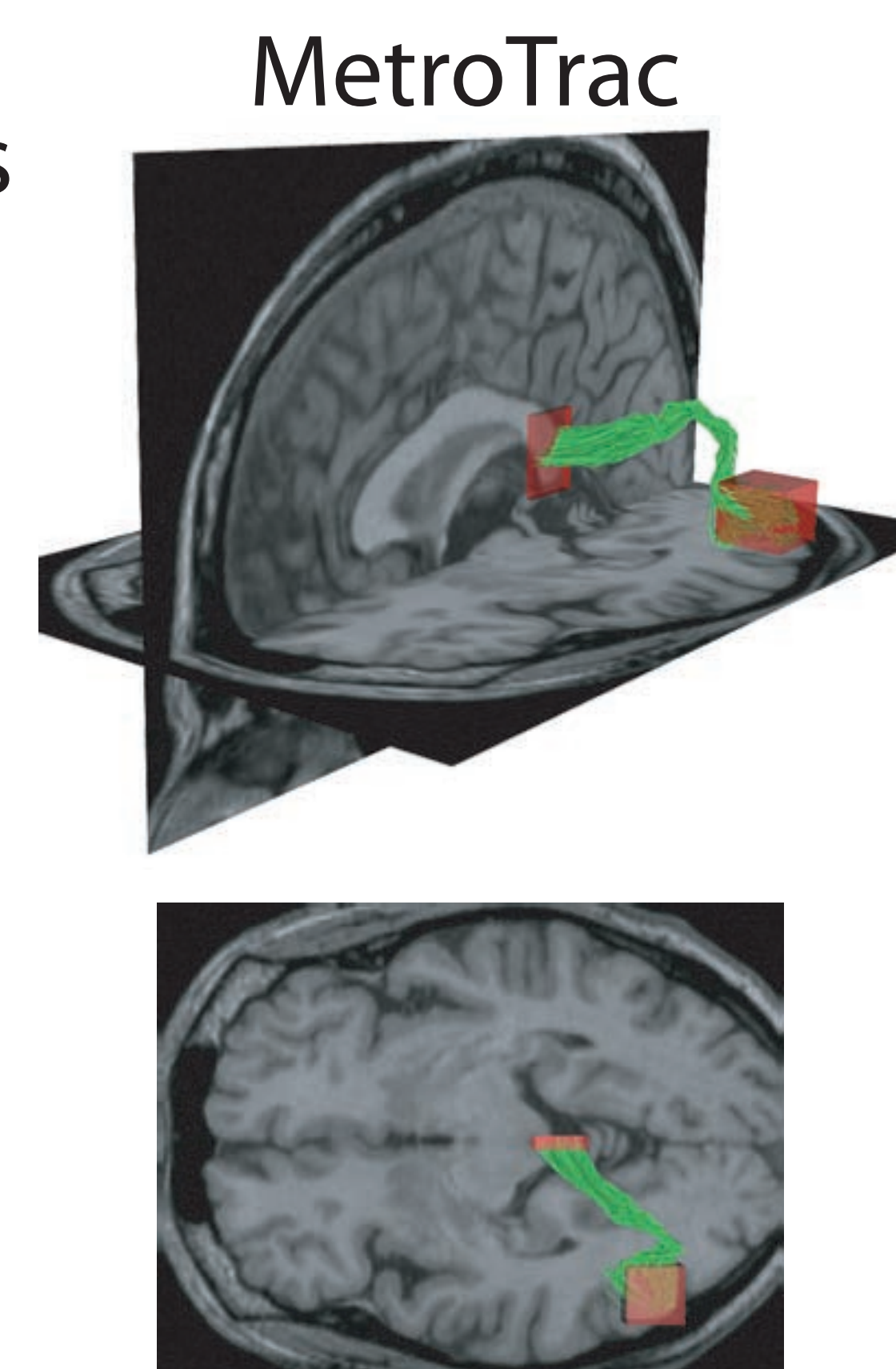
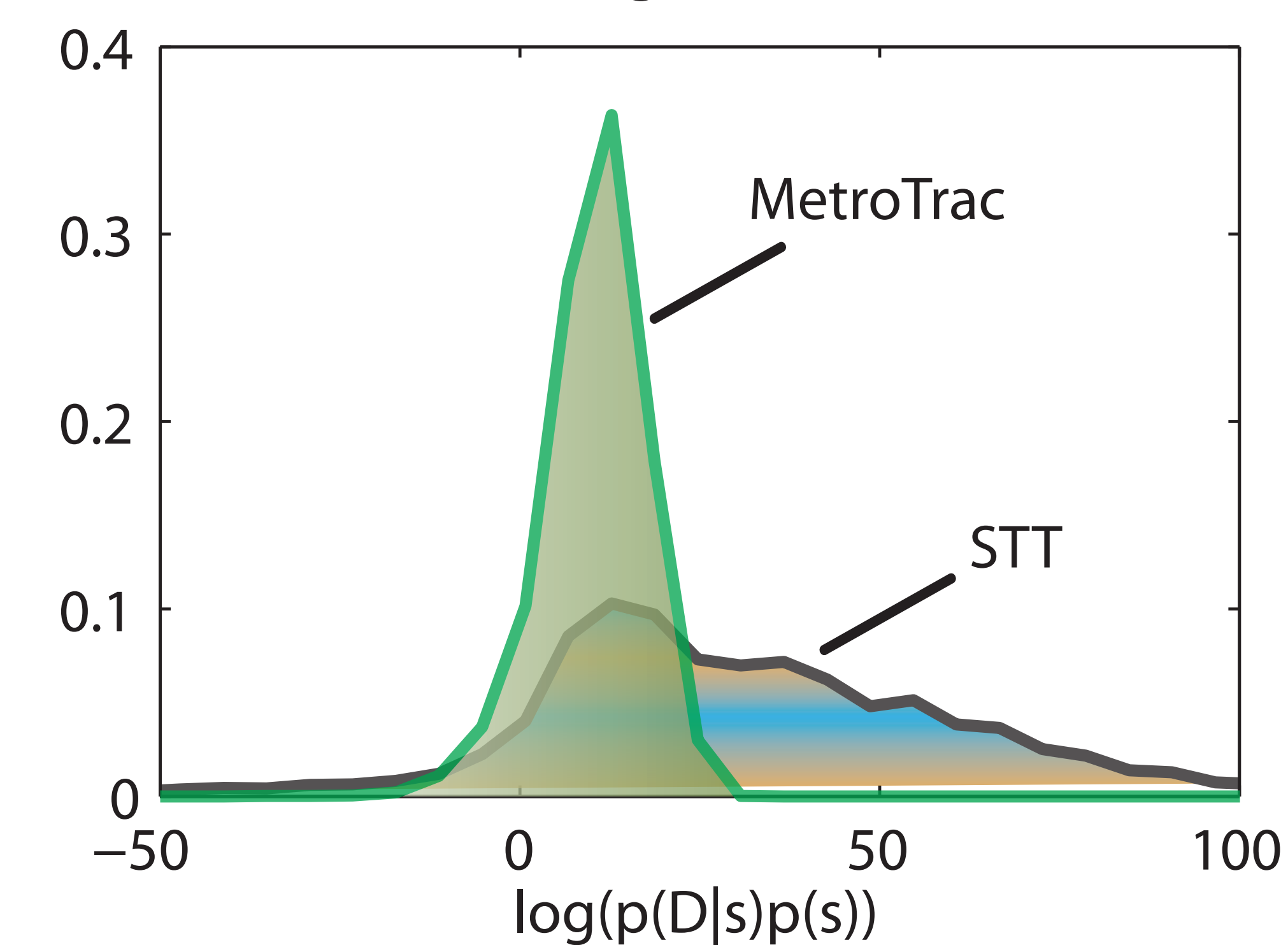
STT tracts were seeded with uniform spacing (1mm) in the entire left hemisphere, with blue tracts intersecting the splenium and orange tracts intersecting a region containing left MT+.

Unlike STT, **MetroTrac** sampled pathways that connected a region around the splenium and a region containing left MT+.

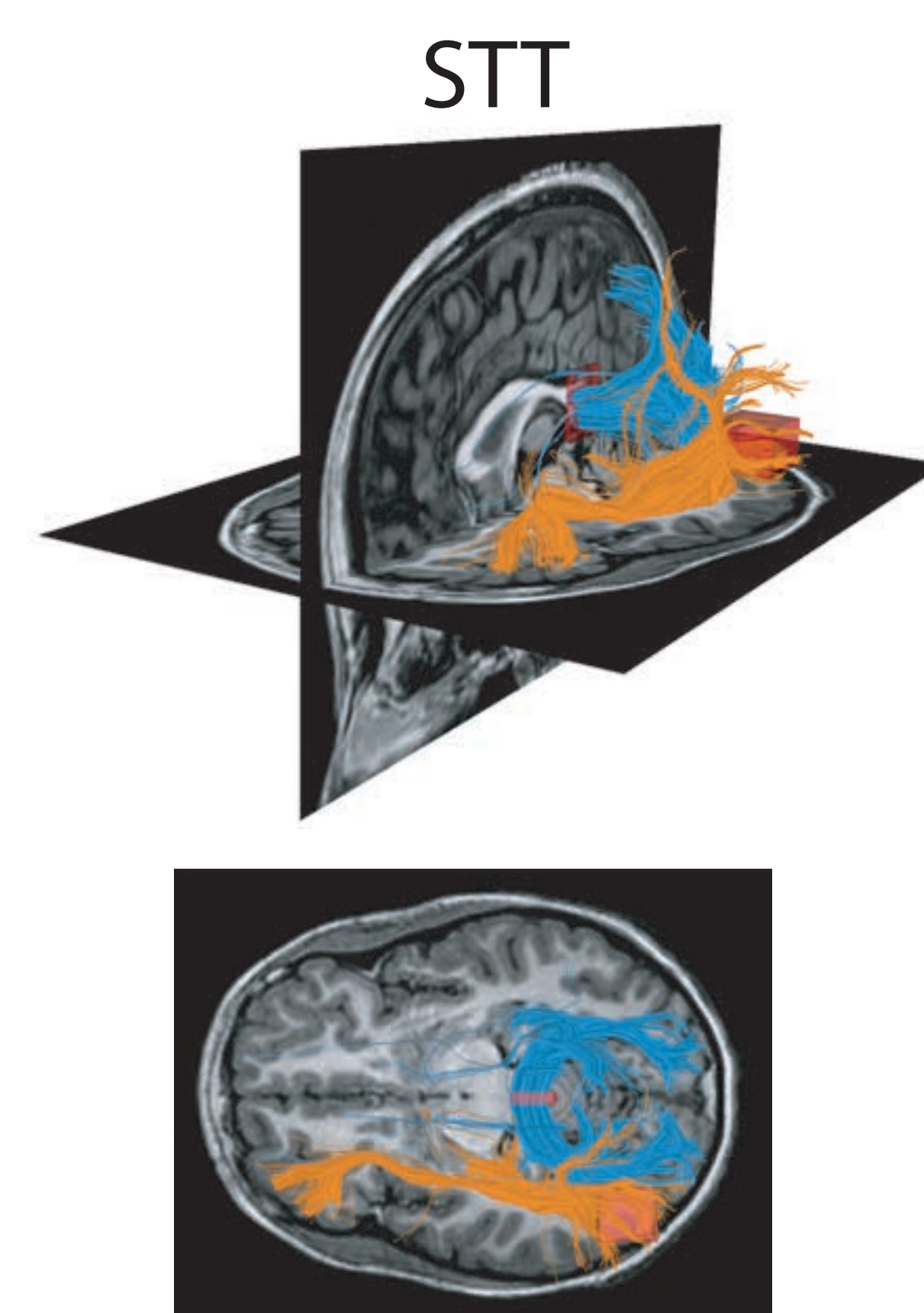
### Example Case 1 of 4 (34y male)



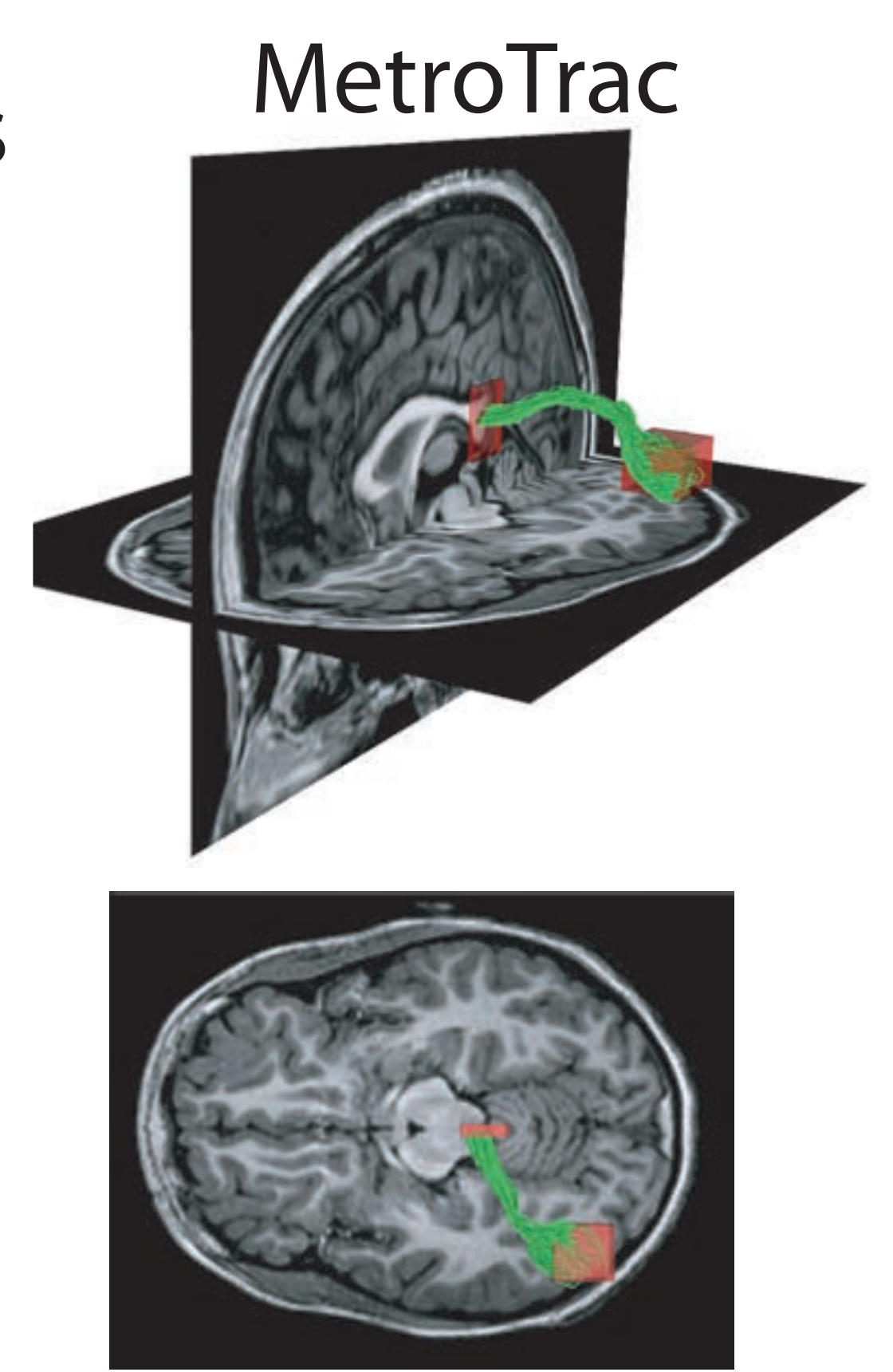
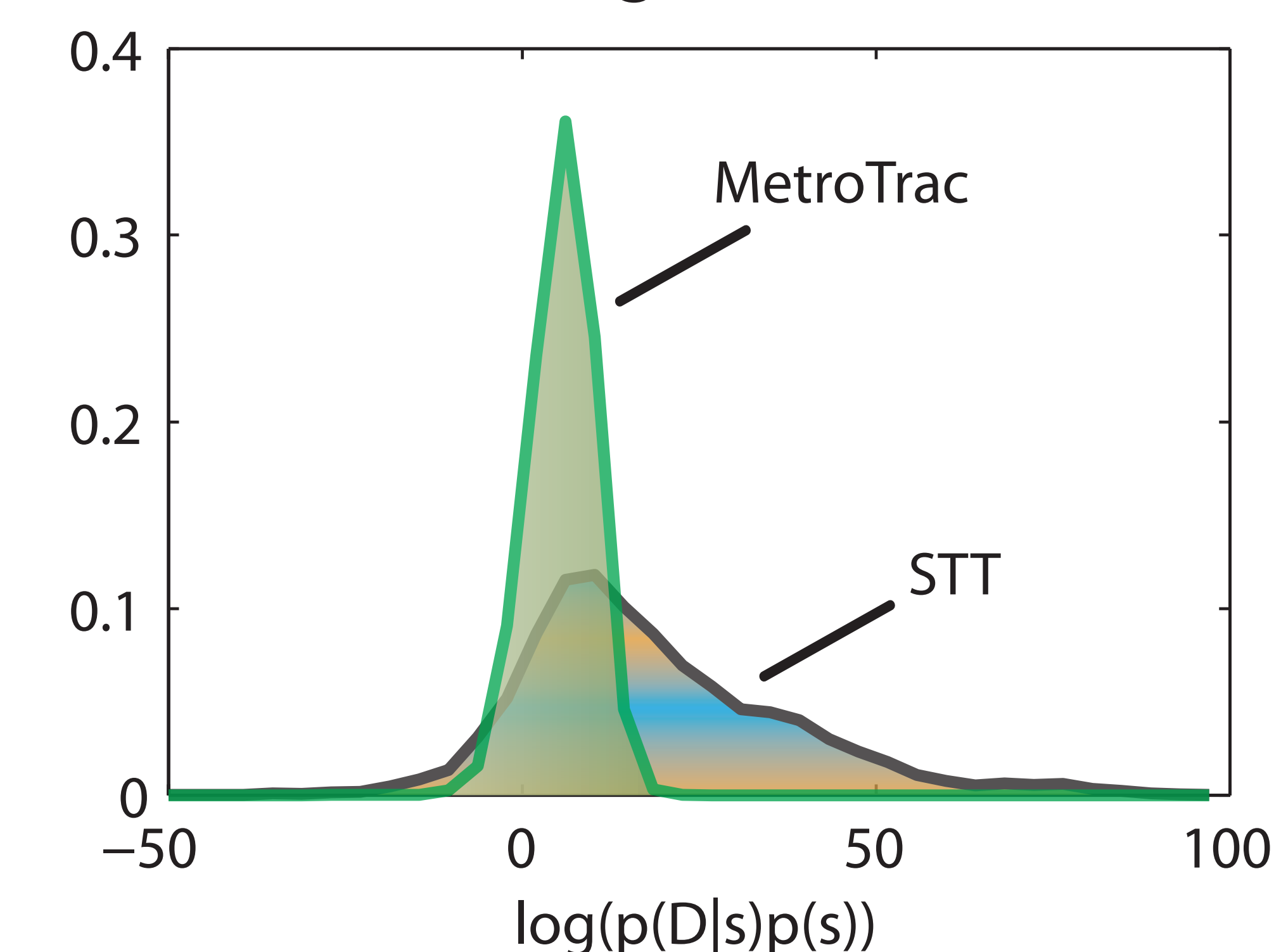
### Normalized Histograms for Path Scores



### Example Case 2 of 4 (11y male)



### Normalized Histograms for Path Scores



## Conclusions

\* MetroTrac implements a novel pathway scoring procedure that adheres to the principles of symmetry and independence.

\* MetroTrac efficiently samples pathways using a Metropolis algorithm to ensure, asymptotically, that path frequency is proportional to score.

\* MetroTrac reveals pathways that are missed by STT.

\* These revealed pathways have scores that are well within the range of the pathways that are found by STT.

## References

- [1] Mori, S., Crain, B.J., Chacko, V.P. & van Zijl, P.C. (1999) Ann. Neurol., 45: 265-269.
- [2] Behrens, T.E.J., M.W. Woolrich, M. Jenkinson, H. Johansen-Berg, R.G. Nunes, S. Clare, P.M. Matthews, J.M. Brady, & S.M. Smith. (2003) Magn. Reson. Med., 50: 1077-1088.
- [3] Parker, G.J.M. & D.C. Alexander. (2005) Philos. Trans. R. Soc. Lond., 360: 893-902
- [4] Dougherty, R.F., M. Ben-Shachar, G. Deutsch, P. Potanina, R. Bammer, & B.A. Wandell. (2005) NYAS, 1064.
- [5] Dougherty, R.F., M. Ben-Shachar, R. Bammer, A.A. Brewer, & B.A. Wandell. (2005) PNAS, 102(20):7350-7355.
- [6] Sherbondy, A., D. Akers, R. Mackenzie, R.F. Dougherty, & B.A. Wandell. (2005) IEEE TVCG, 11(4):419-430
- [7] Metropolis, N., A.W. Rosenbluth, M.N. Rosenbluth, A.H. Teller, E. Teller. (1953) Journal of Chem. Phys., 21:1087-1091

## Acknowledgements

NIH NIGMS Scientist Training Grant  
NIH EY015000  
We thank Pat Hanrahan and Art Owen for the many thought provoking conversations.