Lessons in Multi-site DTI Acquisition- the BIRN experience

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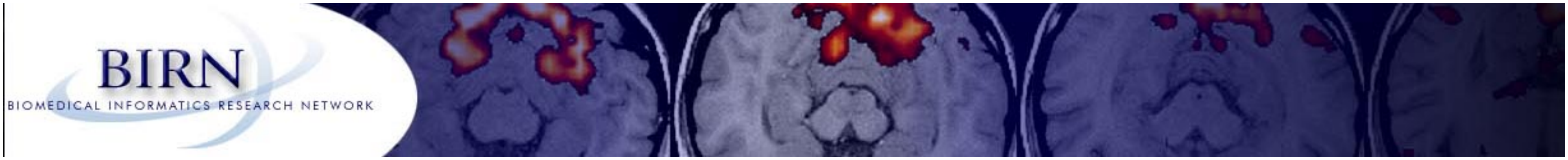


Morphometry BIRN: DTI acquisition

See:
https://xwiki.nbirn.org:8443/bin/view/Morphometry-BIRN/mBIRN_DTI_protocols

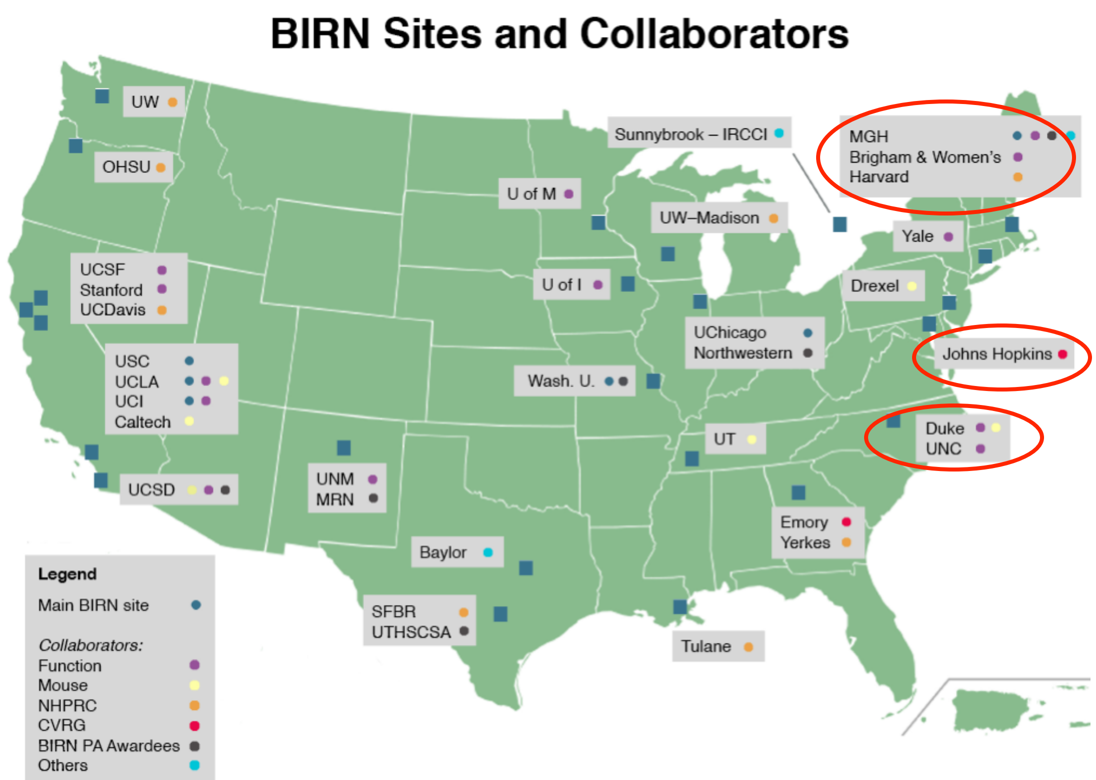
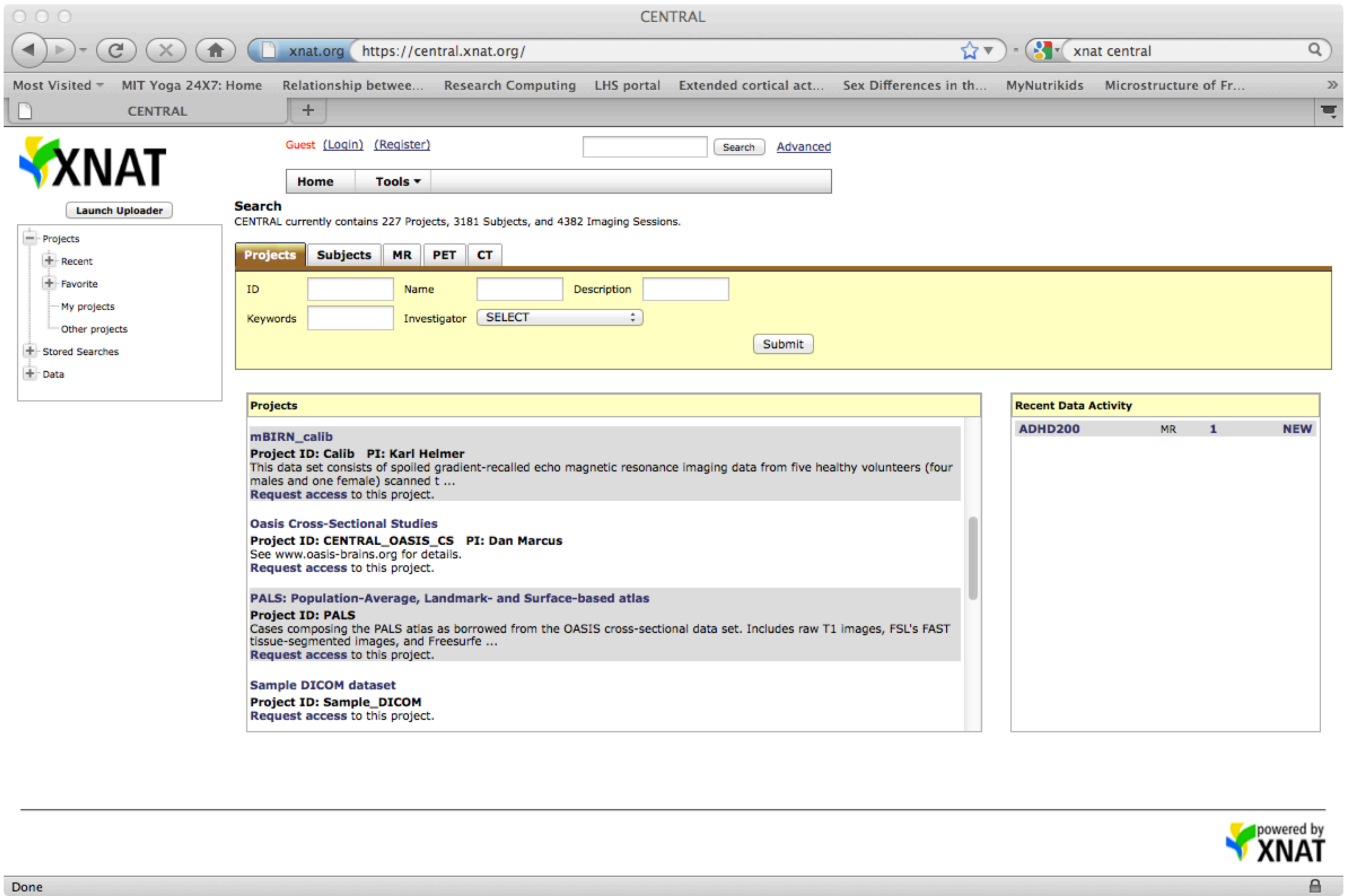


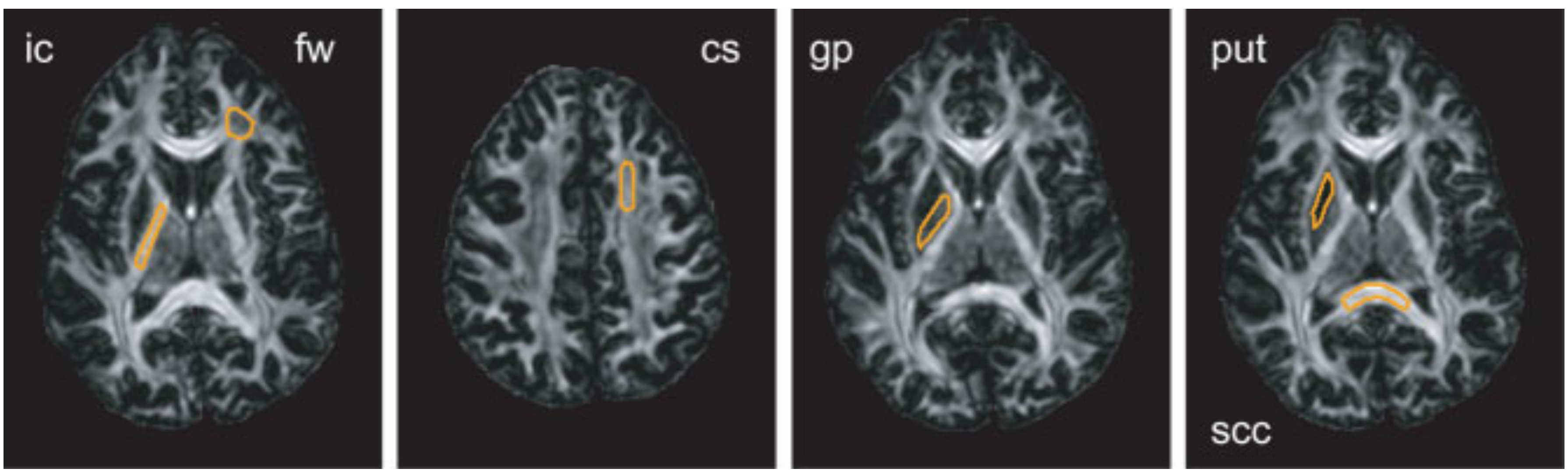
Image Data Repository



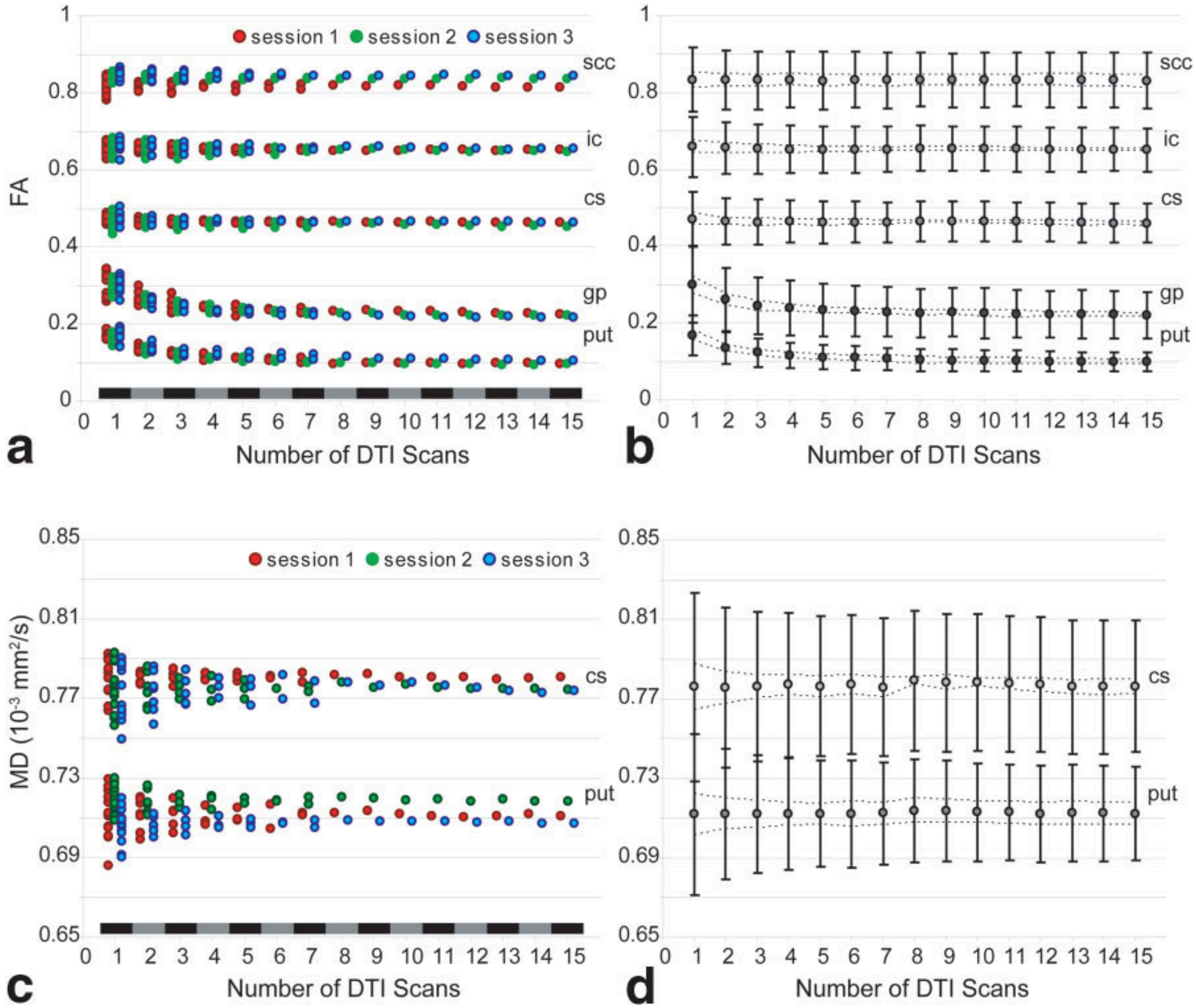
Effects of Signal-to-Noise Ratio on the Accuracy and Reproducibility of Diffusion Tensor Imaging–Derived Fractional Anisotropy, Mean Diffusivity, and Principal Eigenvector Measurements at 1.5T

Jonathan A.D. Farrell, BS,[1–3] Bennett A. Landman, MEng,[4] Craig K. Jones, PhD,[1,2]
Seth A. Smith, PhD,[1,2] Jerry L. Prince, PhD,[2,4,5] Peter C.M. van Zijl, PhD,[1–3]
Susumu Mori, PhD[1,2,4*]

JOURNAL OF MAGNETIC RESONANCE IMAGING 26:756–767 (2007)

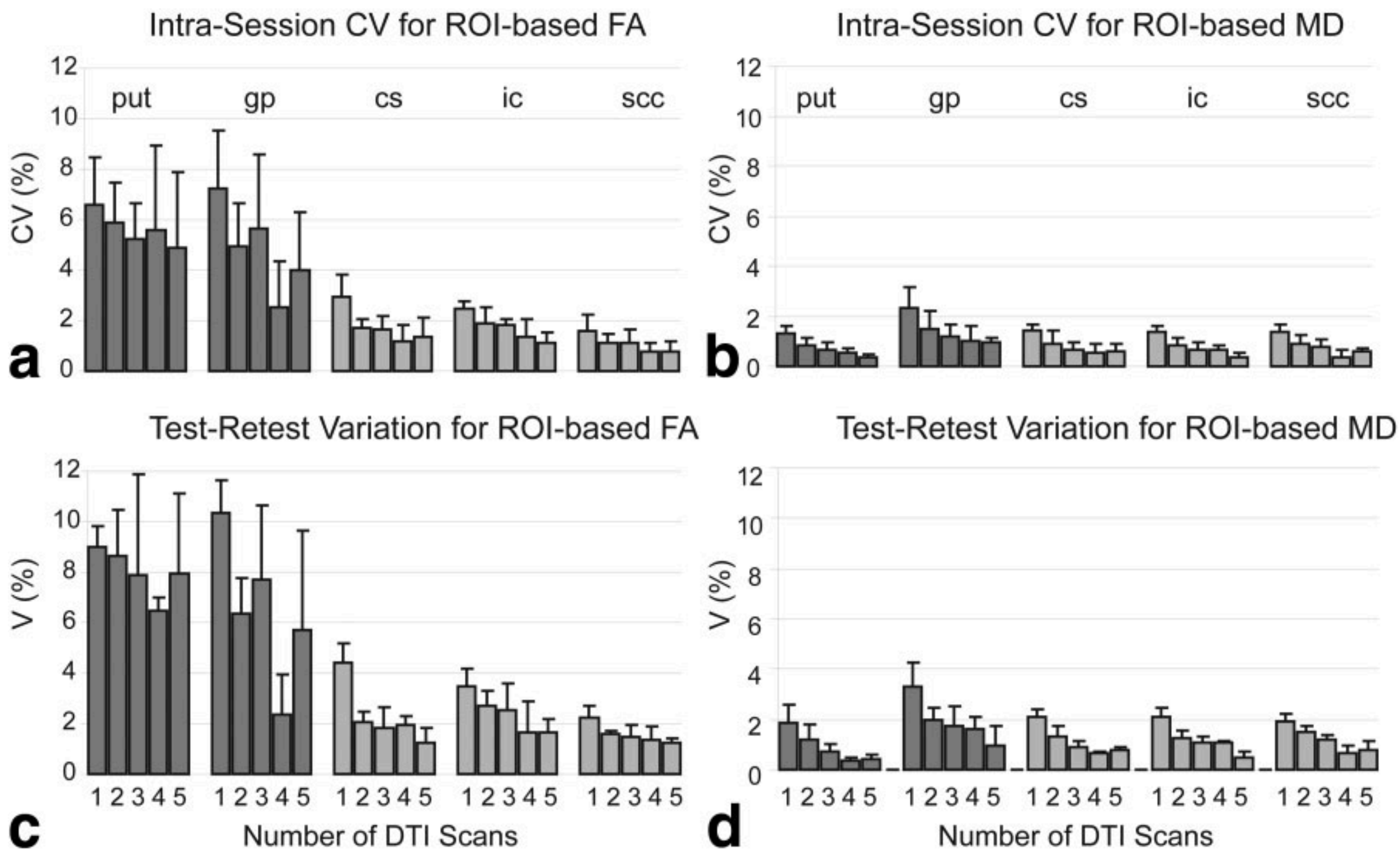


Optimal DTI scan parameters are dictated by the ROI



Farrell et al; 2007

Optimal DTI scan parameters produce reliable results within and across sessions



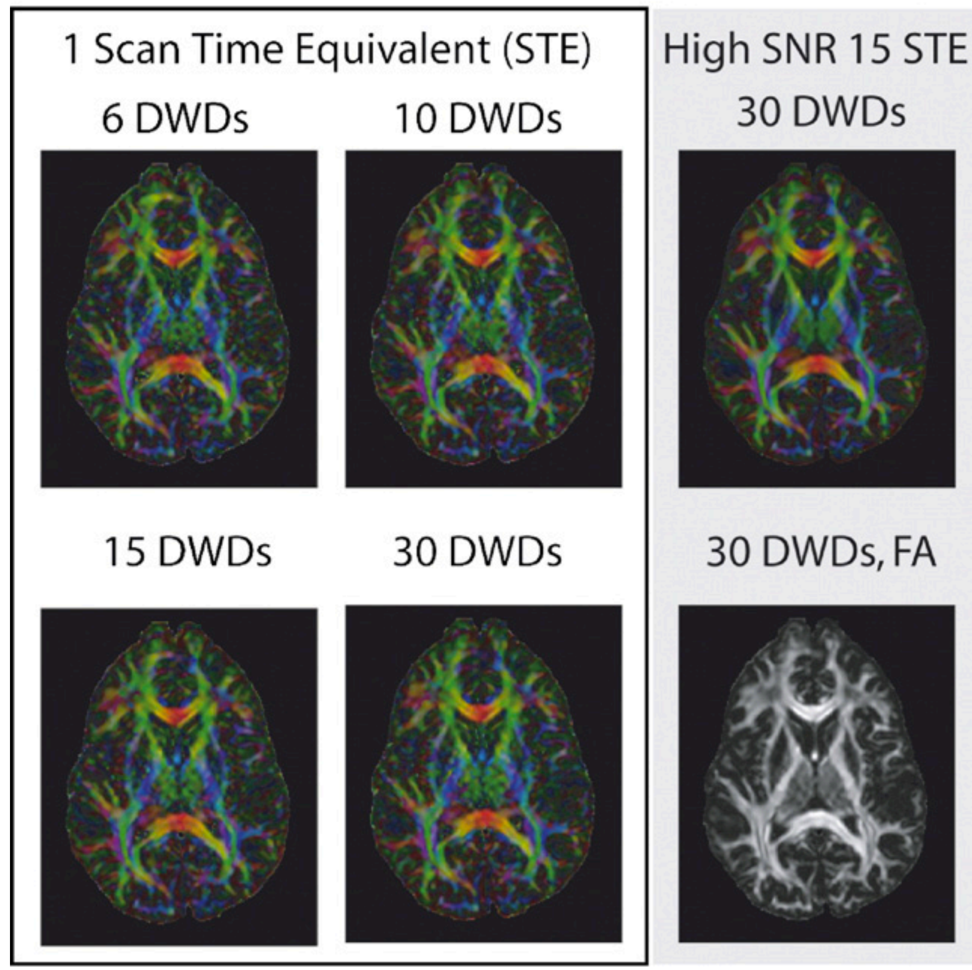
Farrell et al; 2007

Effects of diffusion weighting schemes on the reproducibility of DTI-derived fractional anisotropy, mean diffusivity, and principal eigenvector measurements at 1.5T

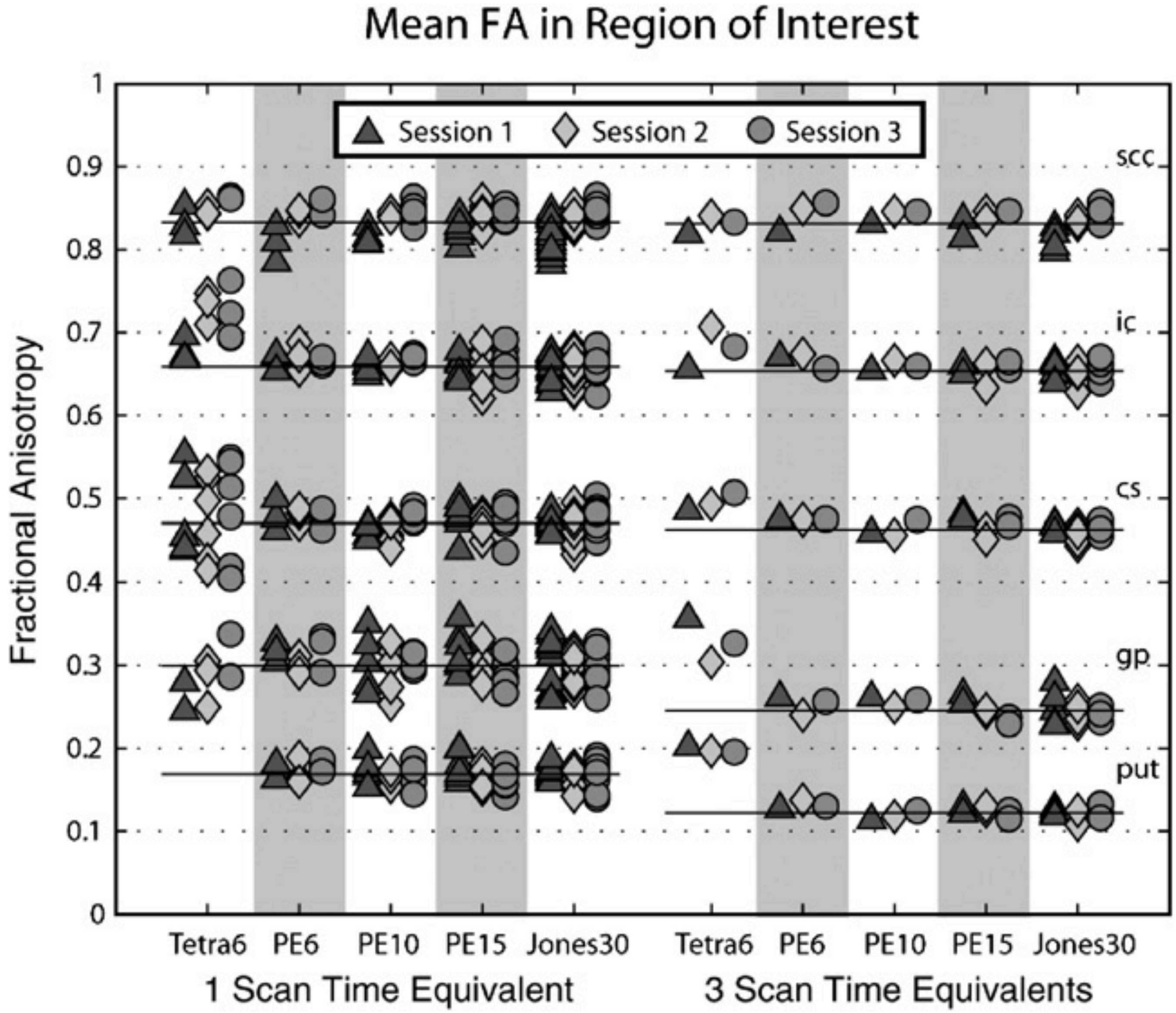
Bennett A. Landman,[a] Jonathan A.D. Farrell,[b,c,d] Craig K. Jones,[b,c] Seth A. Smith,[b,c] Jerry L. Prince,[a,b,e] and Susumu Mori[a,b,c,*]

Differences in DTI contrasts due to different DW schemes are small relative to intra-session variability.

Diffusion Tensor Colormap Images



Well balanced DW schemes give comparable results across sessions



Landman et al; 2007

DTI processing steps that have to be matched across sites or performed at a central site

DTI Data transfer - storage – tracking
Initial quality control

Processing pipeline:
Importing data and transforming to common format
Motion and eddy-current distortion correction
Registration to template
EPI distortion correction
Rotation of b-matrices
Production of “corrected” raw images (interpolation)
Tensor computation (correct weighting)
Robust tensor estimation
Computation of tensor derived variables

Production of tensor data in stereotaxic space

Upload of processed data into shared database

Unpublished presentation from Carlo Pierpoli, 2007

Examples of commonly occurring DWI acquisition problems

- incomplete dataset
- incorrect slice thickness
- incorrect in plane resolution
- incorrect gap between slices
- subject motion
- cardiac pulsation
- EPI ghosting
- image acquisitions have different starting location
- spurious labels in background
- insufficient brain coverage
- b matrix problems
- replicates averaged

Unpublished presentation from Carlo Pierpoli, 2007

Magnetic Resonance in Medicine 51:103–114 (2004)

Comprehensive Approach for Correction of Motion and Distortion in Diffusion-Weighted MRI

G.K. Rohde,[1,3*] A.S. Barnett,[2] P.J. Basser,[1] S. Marenco,[2] and C. Pierpaoli[1]

Patient motion and image distortion induced by eddy currents cause artifacts in maps of diffusion parameters computed from diffusion-weighted (DW) images. A novel and comprehensive approach to correct for spatial misalignment of DW imaging (DWI) volumes acquired with different strengths and orientations of the diffusion sensitizing gradients is presented. This approach uses a mutual information-based registration technique and a spatial transformation model containing parameters that correct for eddy current-induced image distortion and rigid body motion in three dimensions. All parameters are optimized simultaneously for an accurate and fast solution to the registration problem. The images can also be registered to a normalized template with a single interpolation step without additional computational cost. Following registration, the signal amplitude of each DWI volume is corrected to account for size variations of the object produced by the distortion correction, and the *b*-matrices are properly recalculated to account for any rotation applied during registration. Both qualitative and quantitative results show that this approach produces a significant improvement of diffusion tensor imaging (DTI) data acquired in the human brain. Magn Reson Med 51:103–114, 2004. Published 2003 Wiley-Liss, Inc.†

Key words: image registration; mutual information; distortion correction; motion correction; eddy currents

reduce residual eddy current-induced distortions in DW images are based on either field maps or images.

In a field map-based correction scheme, such as that presented by Jezzard et al. (8), one measures the magnetic field produced by the eddy currents and then corrects the distortion using the field map and theoretical models of how field inhomogeneities distort the images. The major obstacle to implementation is the difficulty of rapidly acquiring reliable field maps.

In an image-based registration scheme, one uses a cost function Q to measure how well the images are spatially aligned. First, a target image is chosen as a reference for all other images in the data set (source images). Because it is usually less distorted and has a higher signal-to-noise ratio (SNR) than the heavily DW images, the image acquired with no diffusion sensitization (the T_2-weighted image), is usually used as the target image for registering DW images. Next, using a spatial transformation model, one aligns all other images to the target image by optimizing a cost function. Image-based registration schemes differ from each other in terms of 1) the definition of Q, 2) the types of transformations applied to the image in searching for the

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NeuroImage

www.elsevier.com/locate/ynimg
NeuroImage 26 (2005) 673–684

Estimating intensity variance due to noise in registered images: Applications to diffusion tensor MRI

Gustavo K. Rohde,[a,b,*] Alan S. Barnett,[c] Peter J. Basser,[a] and Carlo Pierpaoli[a]

[a] *STBB/LIMB/NICHD, National Institutes of Health, Building 13, Room 3w16, 13 South Drive, Bethesda, MD 20892, USA*
[b] *Applied Mathematics and Scientific Computation Program, University of Maryland, College Park, MD 20742, USA*
[c] *NIMH, National Institutes of Health, Bethesda, MD 20892, USA*

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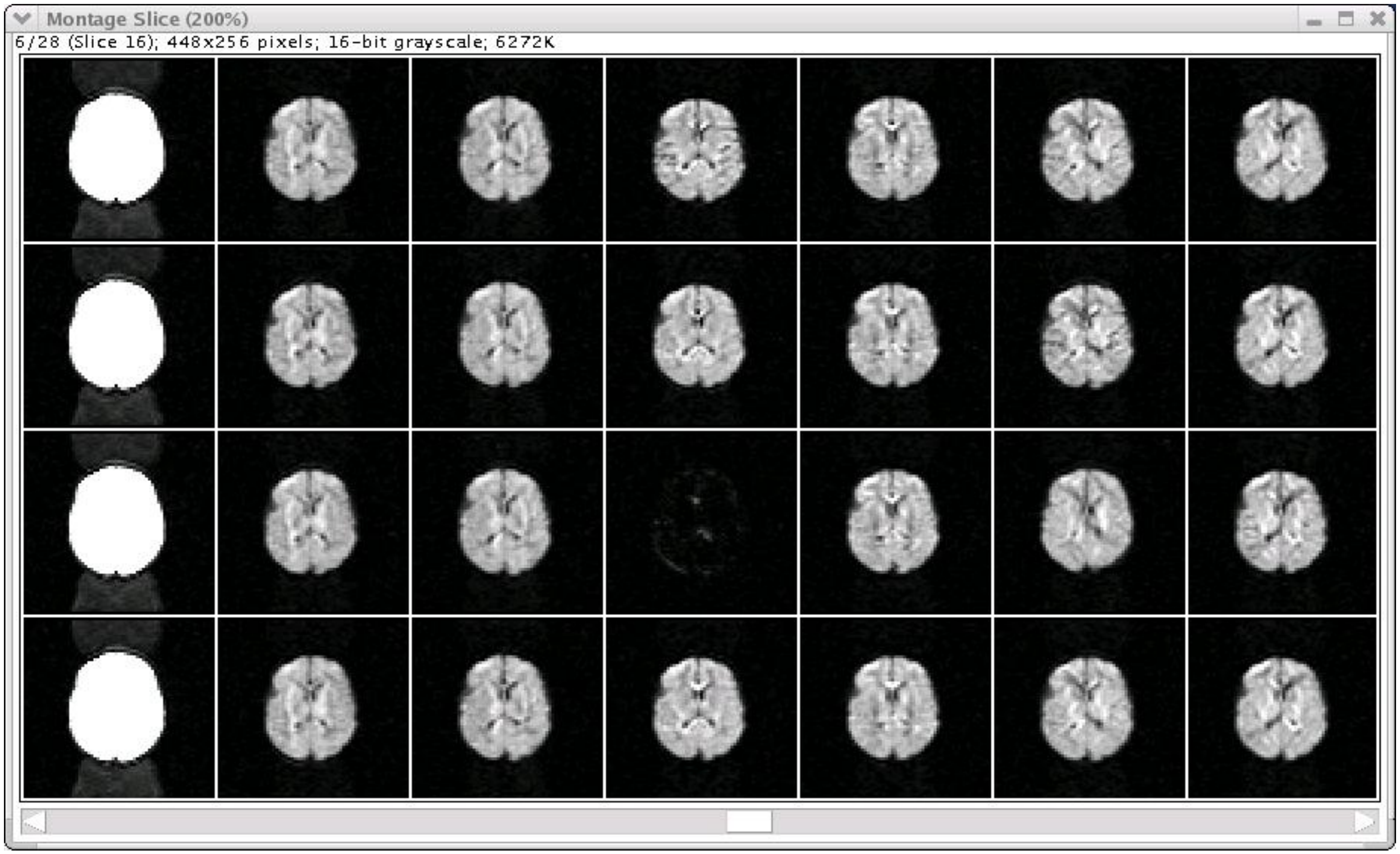
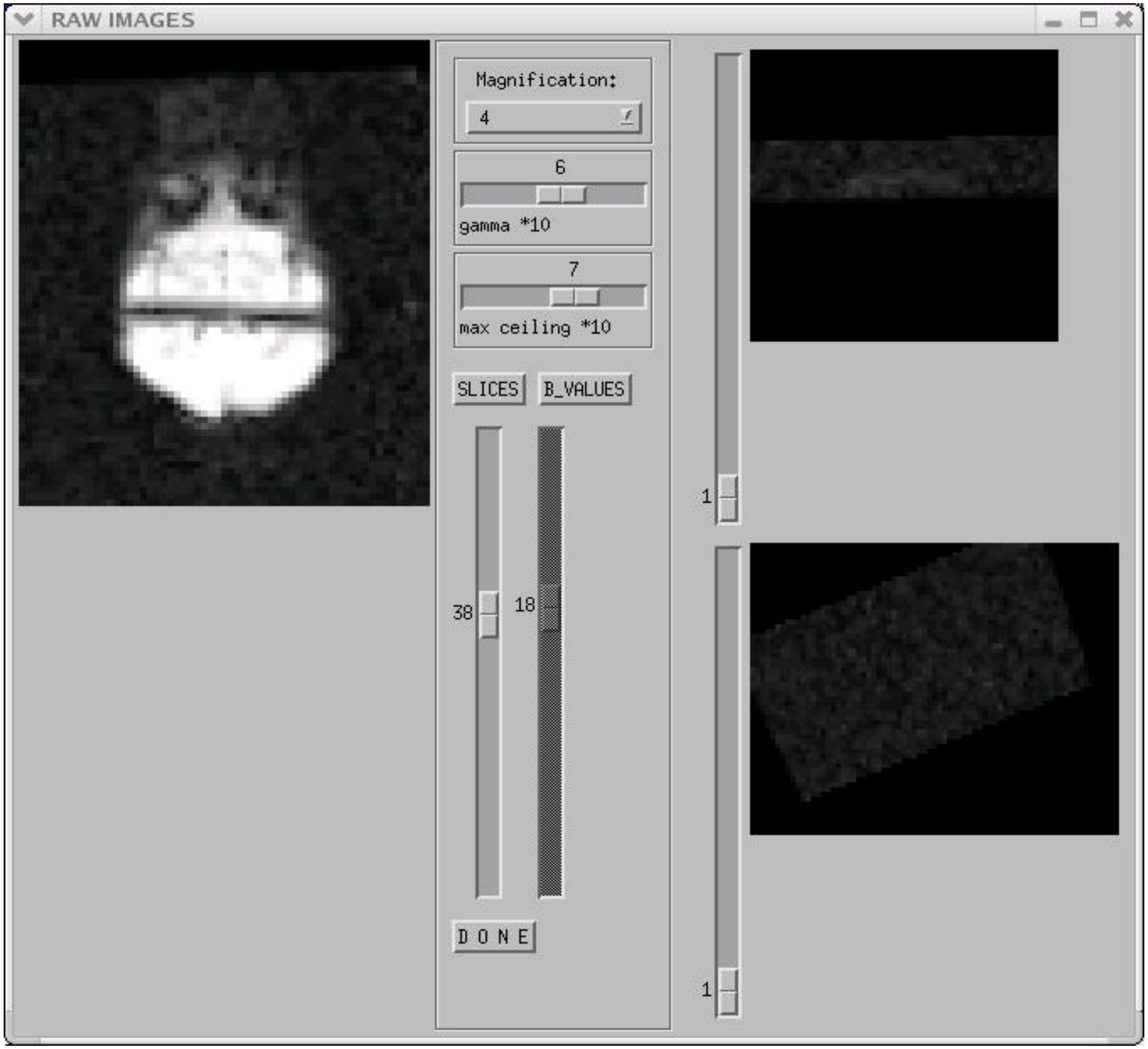
Data set with a corrupted image



Unpublished presentation from Carlo Pierpoli, 2007

Artifact after registration



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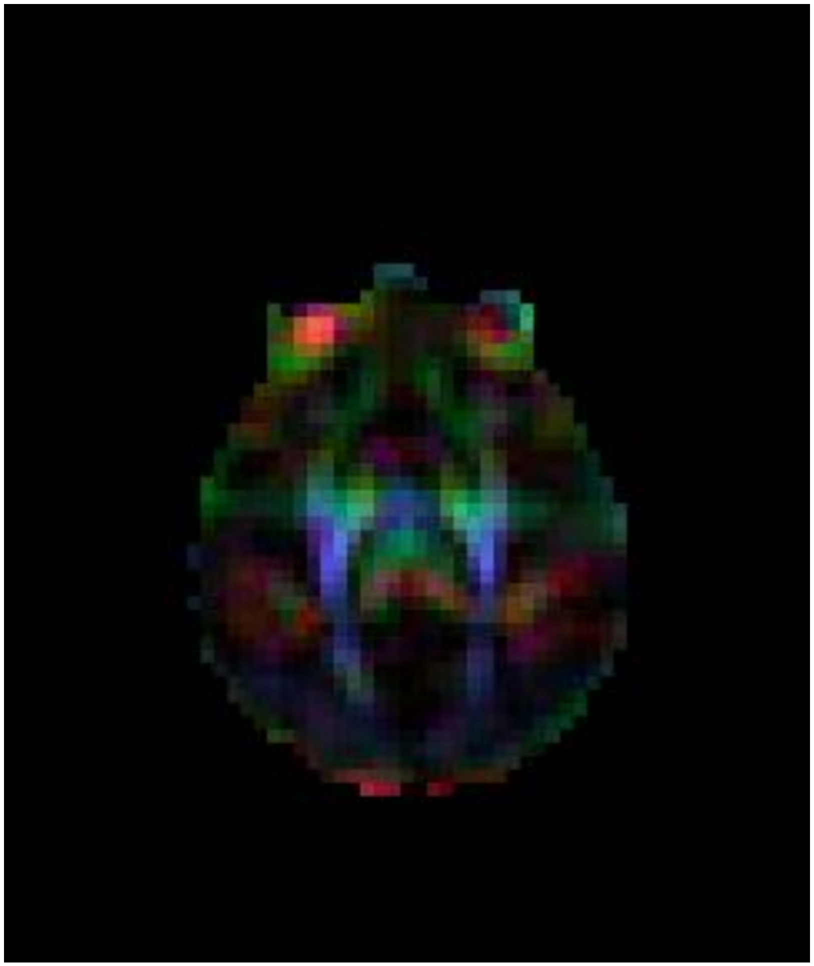
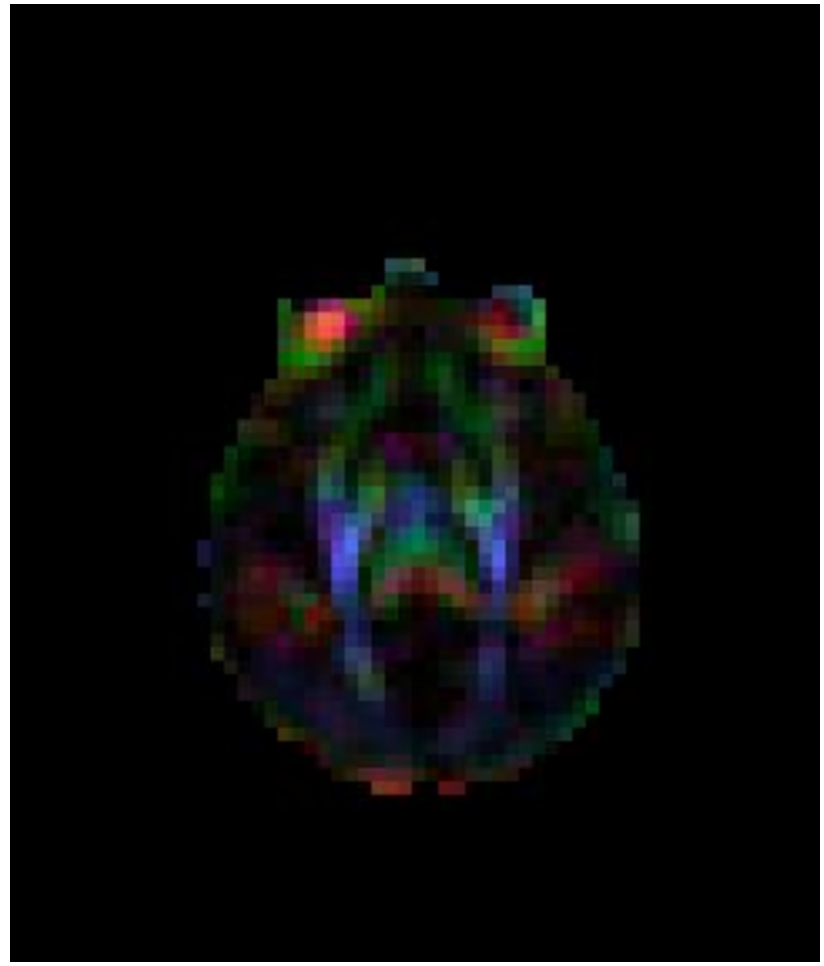
DEC MAP



Conventional tensor fitting



Robust tensor fitting using RESTORE

Unpublished presentation from Carlo Pierpoli, 2007

Magnetic Resonance in Medicine 53:1088–1095 (2005)

RESTORE: Robust Estimation of Tensors by Outlier Rejection

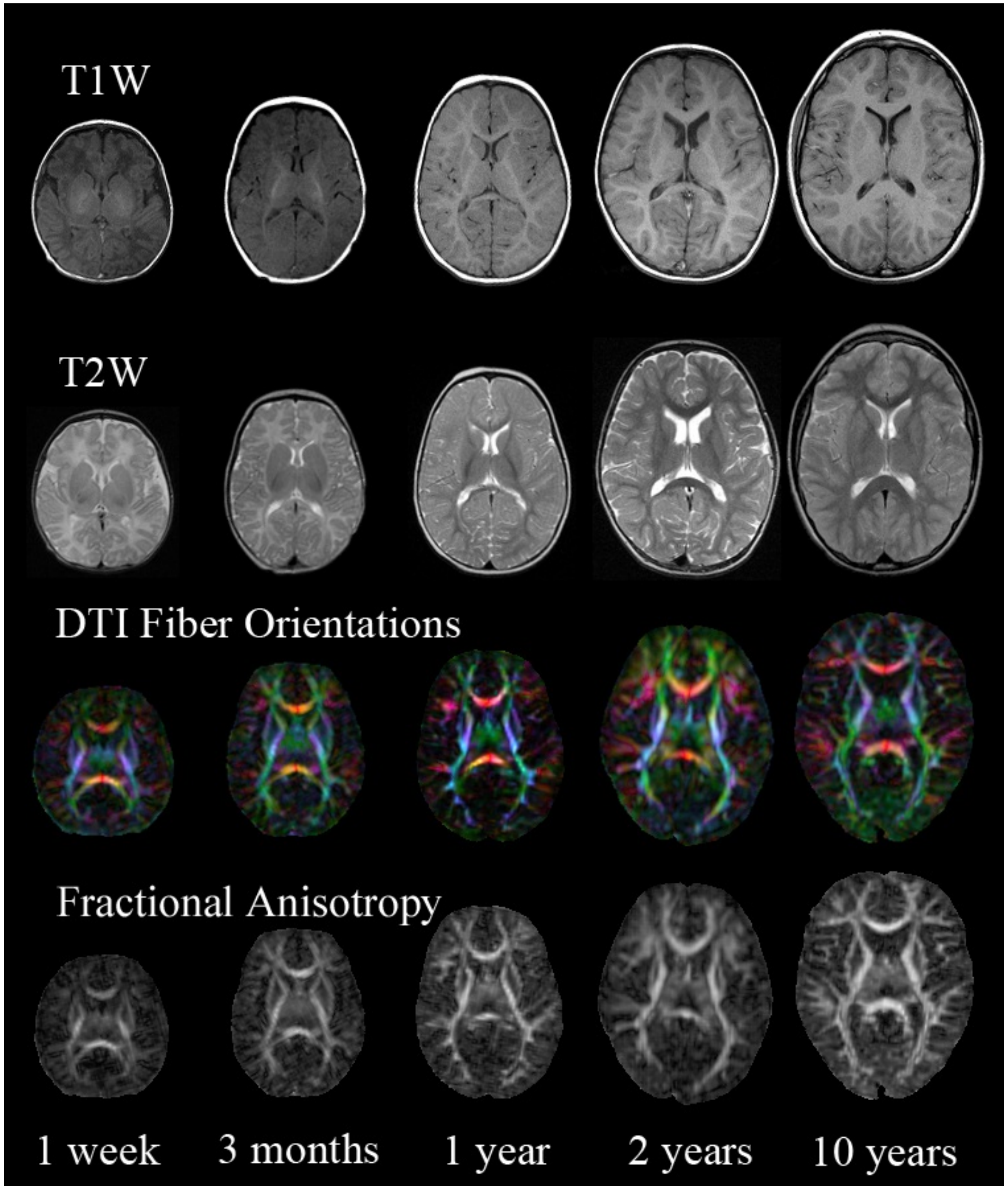
Lin-Ching Chang,[1] Derek K. Jones,[1,2] and Carlo Pierpaoli[1]*

Signal variability in diffusion weighted imaging (DWI) is influenced by both thermal noise and spatially and temporally varying artifacts such as subject motion and cardiac pulsation. In this paper, the effects of DWI artifacts on estimated tensor values, such as trace and fractional anisotropy, are analyzed using Monte Carlo simulations. A novel approach for robust diffusion tensor estimation, called RESTORE (for robust estimation of tensors by outlier rejection), is proposed. This method uses iteratively reweighted least-squares regression to identify potential outliers and subsequently exclude them. Results from both simulated and clinical diffusion data sets indicate that the RESTORE method improves tensor estimation compared to the commonly used linear and nonlinear least-squares tensor fitting methods and a recently proposed method based on the Geman–McClure M-estimator. The RESTORE method could potentially remove the need for cardiac gating in DWI acquisitions and should be applicable to other MR imaging techniques that use univariate or multivariate regression to fit MRI data to a model. Magn Reson Med 53:1088–1095, 2005. Published 2005 Wiley-Liss, Inc.†

Key words: robust estimation; outliers; trace; anisotropy; diffusion; tensor

not account for signal perturbations and potential outliers that originate from artifacts. While the signal variability produced by thermal noise is approximately Gaussian distributed (3), signal variability produced by physiologic noise and other artifacts does not have a known parametric distribution and currently cannot be modeled. Situations in which experimental errors do not follow a Gaussian distribution, or are unknown, are generally addressed statistically by using "robust" estimators, which are less sensitive to the presence of outliers.

Surprisingly, the use of robust estimators has been largely neglected by the DT-MRI community. We are aware of only one robust tensor estimation approach recently proposed by Mangin et al. (4), which is based on the well-known Geman-McClure M-estimator (5) (we will refer to Mangin's approach as GMM in this paper). This approach uses an iteratively reweighted least-squares fitting in which the weight of each data point is set to a function of the residuals of the previous iteration. The GMM method ensures that potentially artifactual data points having large residuals are given lower weights in



NIH MRI Study of Normal Brain Development

Public Website:
http://www.brain-child.org/

Unpublished presentation by Carlo Pierpoli, 2007

Lessons learned

No matter how carefully the study is planned expect relatively large variability in the quality of the acquired data

Run a pilot study with all the sites involved prior to starting data collection

Use strict quality control criteria

Set up a robust data processing pipeline to reduce variability across sites

- **The University of Iowa**
  - Nancy C. Andreasen, M.D. Ph.D.
  - Beng C. Ho, M.D.
  - Vincent A Magnotta, Ph. D.
  - Thomas Wassink, M.D.
- **Massachusetts General Hospital**
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  - Larry Siedman, Ph.D.
  - Laura Kunkel, M.D.
- **The University of Minnesota**
  - Kelvin O. Lim, M.D.
  - Bryon Mueller, Ph.D.
  - S. Charles Schulz, M.D.
  - Tonya White, M.D.
- **The University of New Mexico / MIND Institute**
  - Jeremy Bockholt
  - Juan Bustillo, M.D.
  - Vince Calhoun, Ph.D.
  - Vince Clark, Ph.D.
  - John Lauriello, M.D.

White Matter Abnormalities in Schizophrenia

Summary of 50+ Studies

White, Nelson, Lim (2009)

Authors	Methods	Results
Kumra et al. (2004)	ROI	↓ FA in bilat. frontal and occipital white matter regions
Kumra et al. (2005)	Voxel-based	↓ FA in L anterior cingulate region
White et al. (2007)	Voxel-based	↓ FA in L hippocampus
Kyriakopoulos et al. (2008)	Voxel-based	↓ FA in bilateral parietal association cortices and L middle cerebellar peduncle
Kendi et al. (2008)	ROI	No difference in FA in fornix but ↓ volume of the fornix
White et al. (2009)	Pothole	Greater number of potholes, more pronounced in the corpus callosum
James et al. (2011)	Voxel-based	Wide-spread reductions in FA

University of Minnesota

Patients n = 27

Controls n = 22

Massachusetts General Hospital

Patients n = 28

Controls n = 21

University of New Mexico

Patients n = 41

Controls n = 43

University of Iowa

Patients n = 19

Controls n = 52

	Patients (n = 114)		Controls (n = 138)	
	Chronic (n = 83)	**First-Episode (n = 31)**	**Chronic Control (n = 95)**	**First-Episode Control (n = 43)**
Age (years, SD)	36.4 (11.0)	25.2 (6.7)	34.0 (11.3)	25.2 (6.6)
Sex (M / F)	62 / 21	22 / 9	57 / 38	24 / 19
Hand (R / L / Both)	73 / 3 / 6	26 / 3 / 1	86 / 5 / 3	41 / 2 / 0
WRAT 3rd (Reading)	46.8 (6.2)	47.1 (6.6)	50.8 (4.5)	50.2 (3.9)
Father's Education	14.3 (3.3)	13.9 (4.7)	15.0 (3.7)	14.6 (2.3)
Mother's Education	13.3 (3.6)	14.1 (3.2)	13.8 (2.9)	14.1 (2.3)
BMI	28.9 (6.7)	24.9 (3.0)	26.4 (5.3)	24.1 (4.2)

Acquisition Parameters at Four sites

	Iowa	MGH	UMinn	NMex
Diffusion Tensor Images				
Scanner	Siemens 3T TRIO	Siemens 1.5 T Sonata	Siemens 3T TRIO	Siemens 1.5 T Sonata
TR (ms)	9,500	8,900	10,500	9800
TE (ms)	90	80	98	86
Voxel Dimensions (mm)	2 x 2 x 2	2 x 2 x 2	2 x 2 x 2	2 x 2 x 2
Diffusion Directions	6	60	12	12
B-Values (s/mm^2)	0 / 1,000	0 / 700	0 / 1,000	0 / 1,000
NEX	4	1	2	4
Bandwidth (Hz/pixel)	1,954	1,860	1,342	1,502

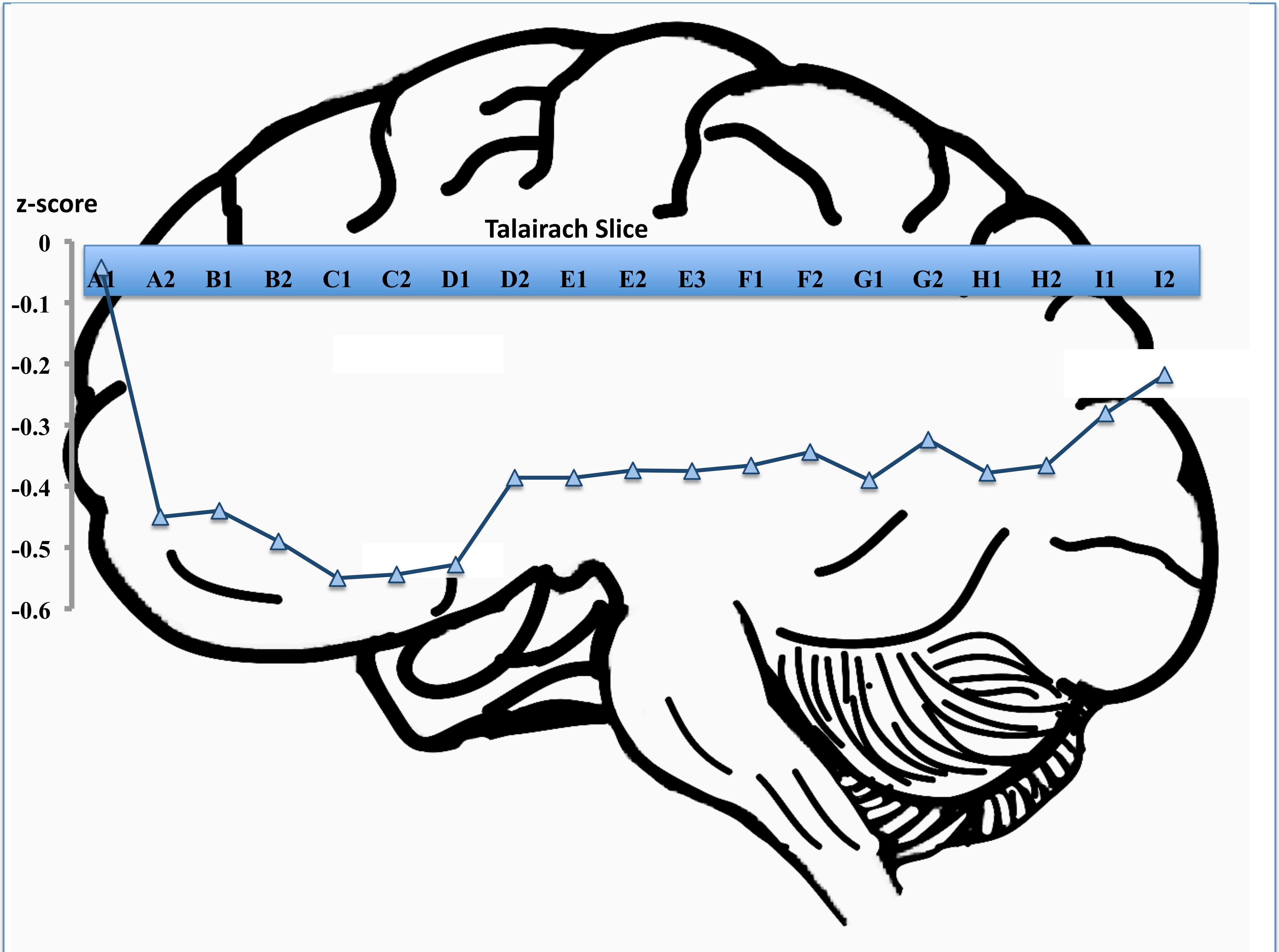
Initial Report:

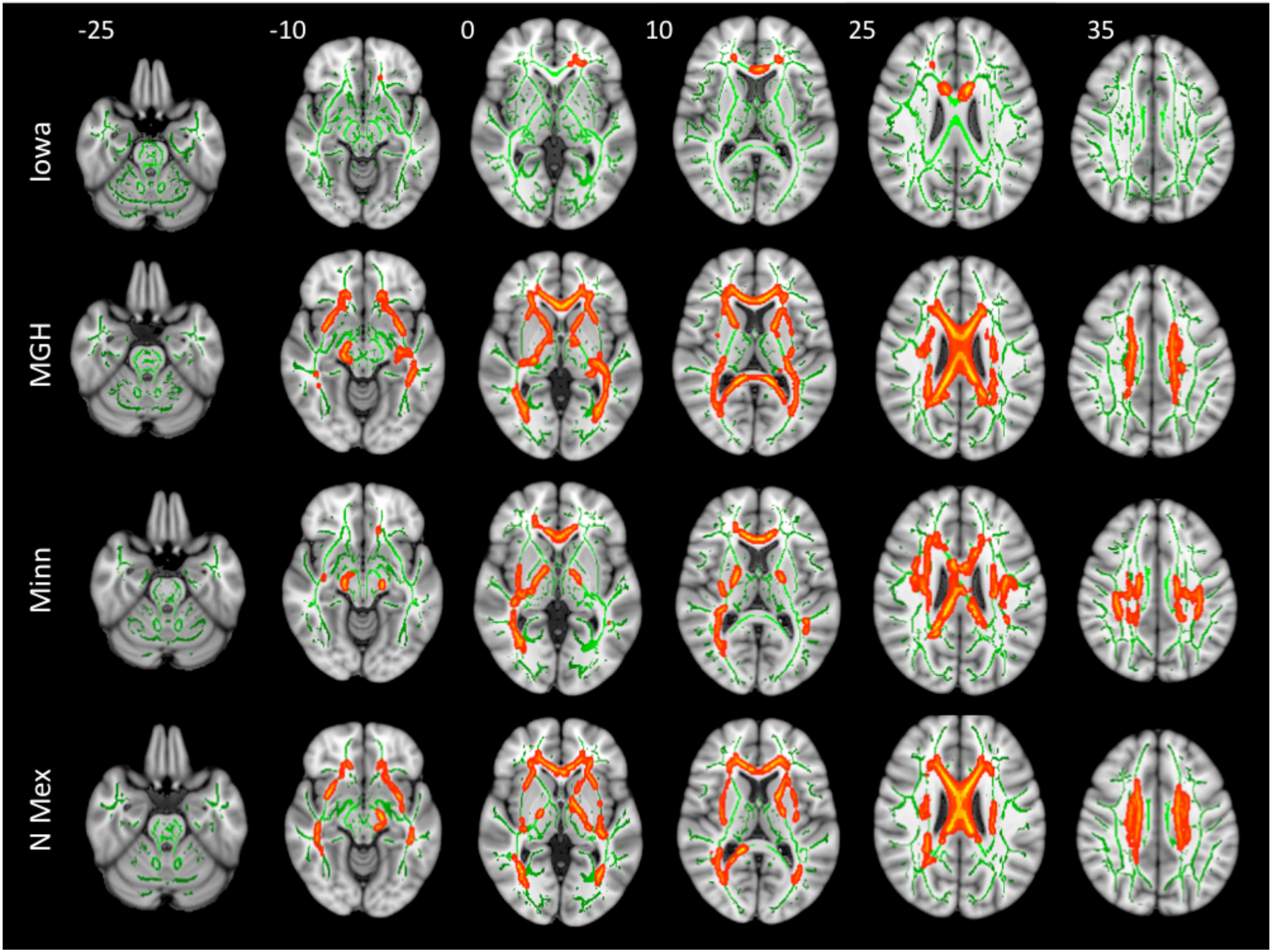
White T, Magnotta VA, Bockholt HJ, et al. Global white matter abnormalities in schizophrenia: a multisite diffusion tensor imaging study. *Schizophrenia Bulletin.* Jan 2011;37(1):222-232.

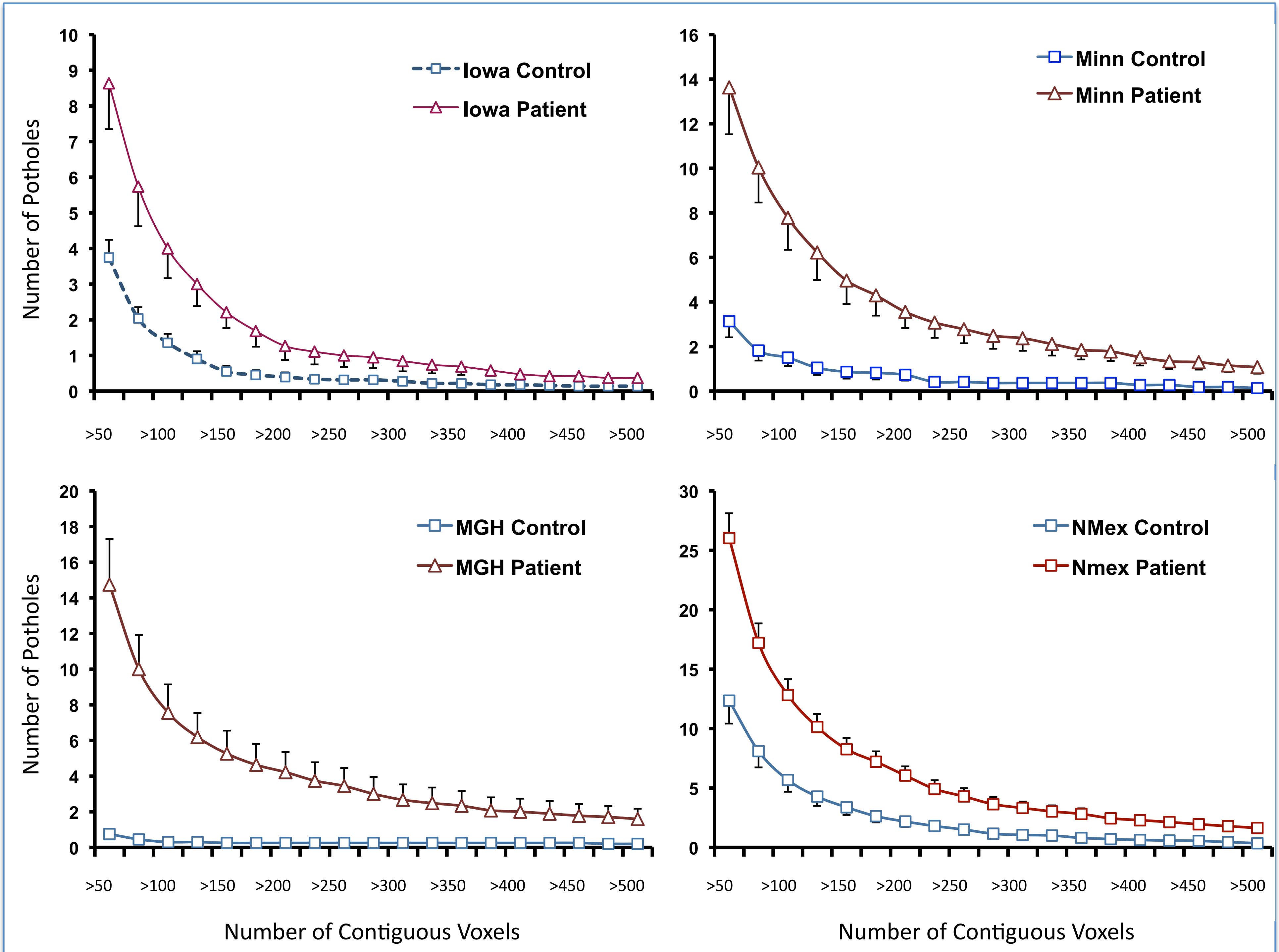
Currently under review:

Spatial Characteristics of White Matter Abnormalities in Schizophrenia

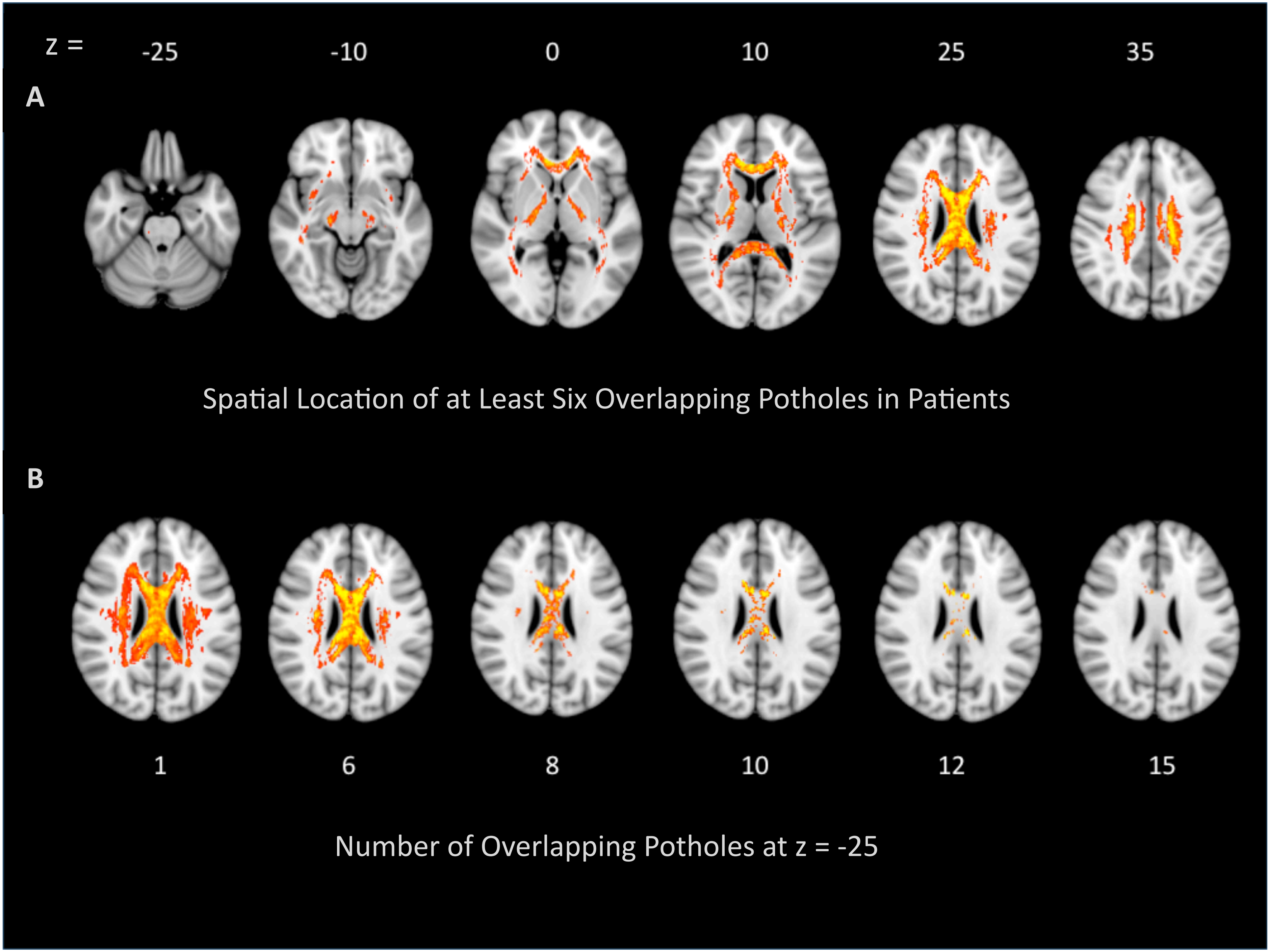
Tonya White, M.D., Ph.D. [1,2], H. Jeremy Bockholt [3,4], Stefan Ehrlich, M.D. [5,6], Beng C. Ho, M.D. [7], Dara S. Manoach [5,8], Vincent P. Clark, Ph.D. [4,9], Randy L. Gollub, M.D., Ph.D. [5,8], Vince D. Calhoun, Ph.D. [4,10], S. Charles Schulz, M.D. [11], Nancy C. Andreasen, M.D., Ph.D. [7], Kelvin O. Lim, M.D. [11], Vincent A. Magnotta, Ph.D. [12]


z-score
Talairach Slice
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
A1
A2
B1
B2
C1
C2
D1
D2
E1
E2
E3
F1
F2
G1
G2
H1
H2
I1
I2


-25
-10
0
10
25
35
Iowa
MGH
Minn
N Mex



Iowa Control
Iowa Patient
Minn Control
Minn Patient
MGH Control
MGH Patient
NMex Control
Nmex Patient
Number of Potholes
Number of Contiguous Voxels
>50
>100
>150
>200
>250
>300
>350
>400
>450
>500


z =
-25
-10
0
10
25
35
A
Spatial Location of at Least Six Overlapping Potholes in Patients
B
1
6
8
10
12
15
Number of Overlapping Potholes at z = -25

Conclusions

- There is considerable evidence that abnormalities in white matter play a significant role in the neuropathology of schizophrenia
- There is considerable heterogeneity in the spatial location of white matter abnormalities in schizophrenia
  - First-episode and early-onset patients have more focal abnormalities
  - It is possible that the heterogeneity in clinical symptoms parallels the heterogeneity in white matter abnormalities.