Likelihood Analysis of Diffusion Weighted MRI

Bennett Landman

Biomedical Engineering

Johns Hopkins University

February 21, 2008

BIRN BIOMEDICAL INFORMATICS RESEARCH NETWORK

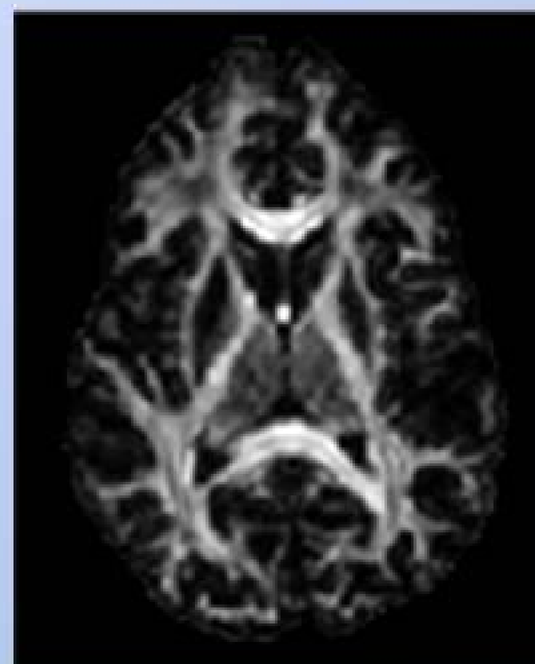
MEDIC

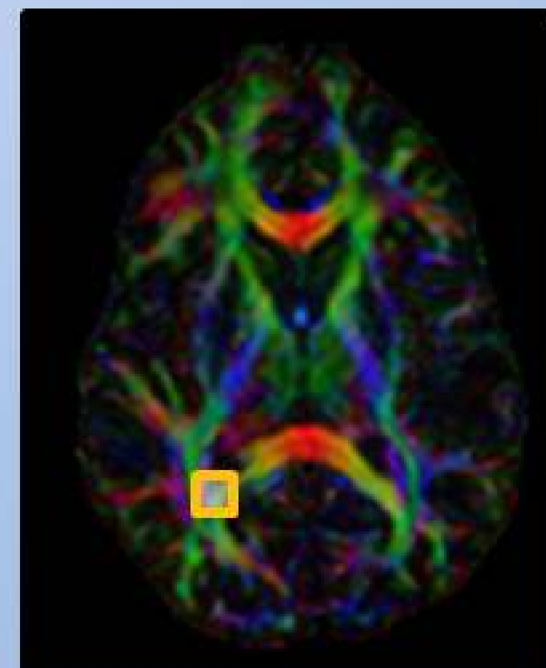
JOHNS HOPKINS MEDICINE

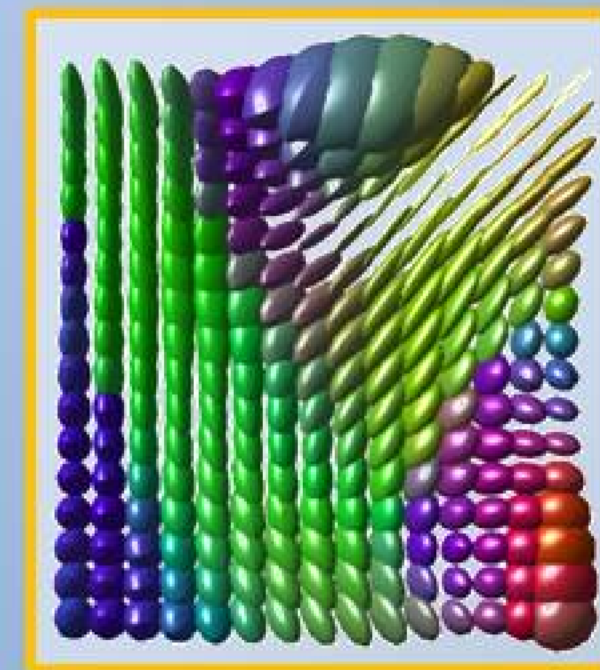
Kennedy Krieger Institute

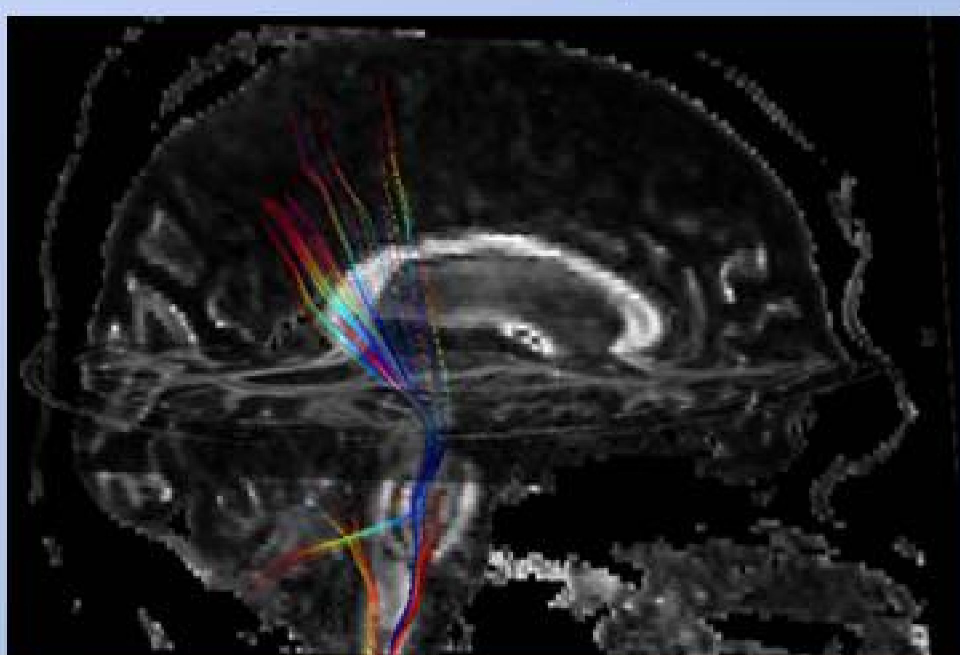
F.M. Kirby Research Center for Functional Brain Imaging

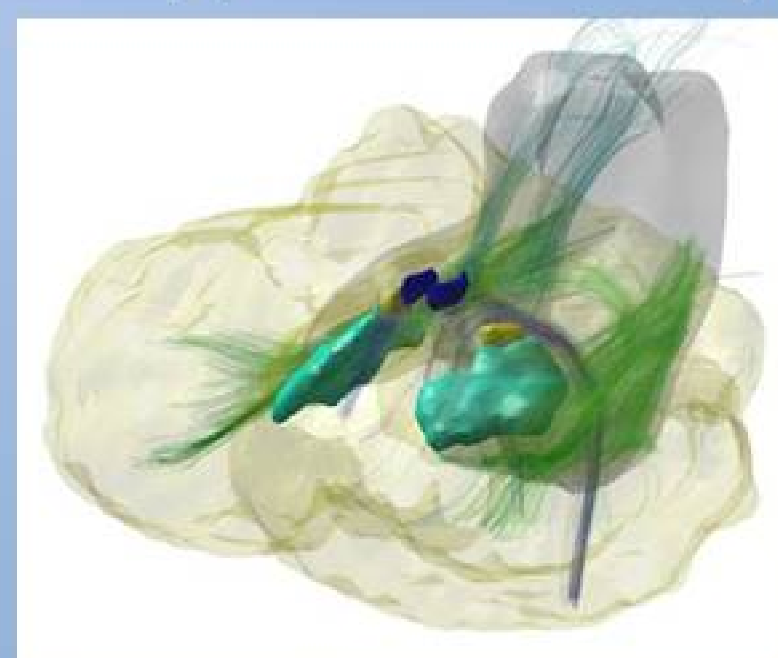
Revealing Tissue Architecture









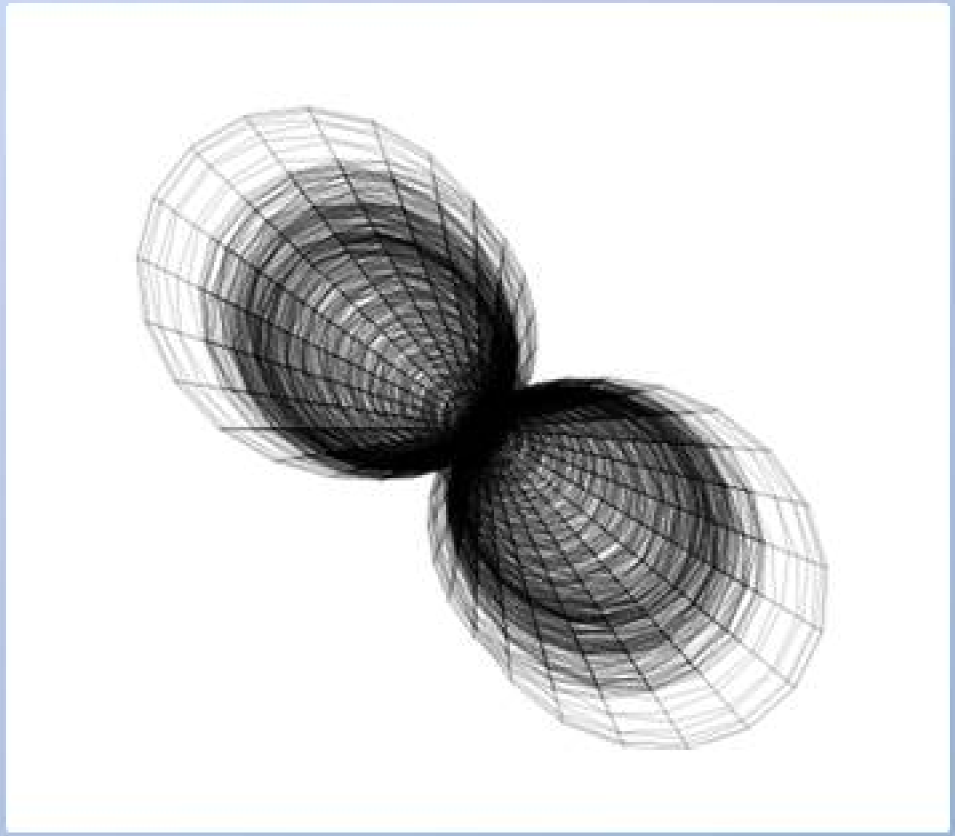


Noise Corrupts Estimated Structure

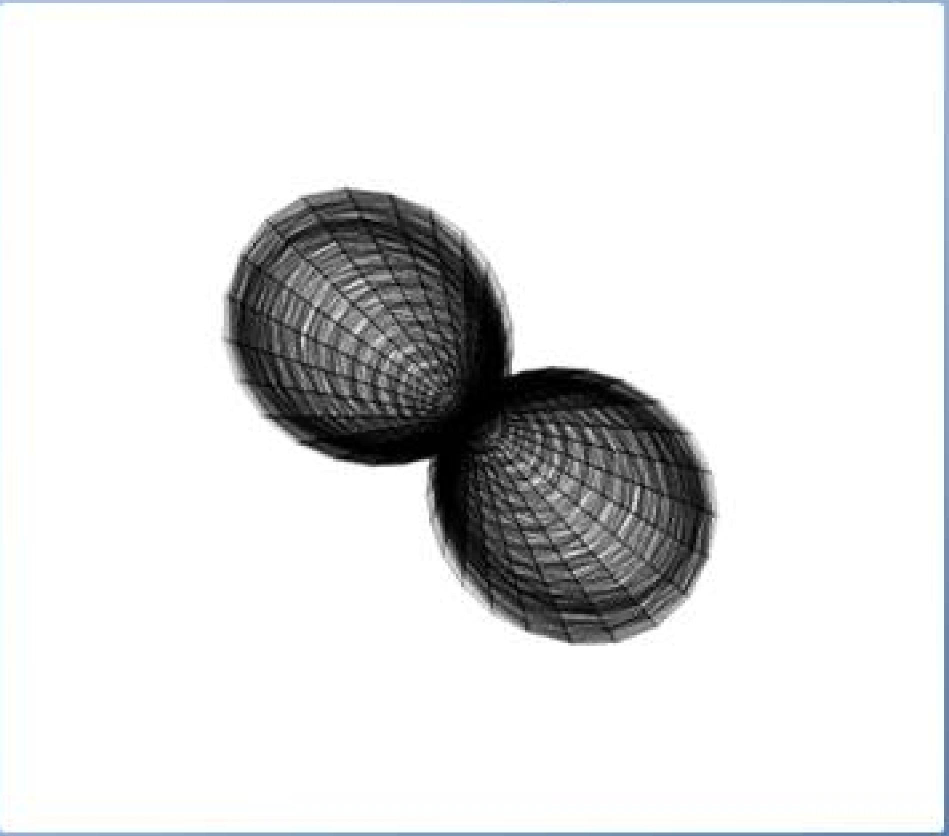
Landman et al. 2008a

One White Matter Voxel Scanned 22 Times Over 3 Days

Traditional Estimator

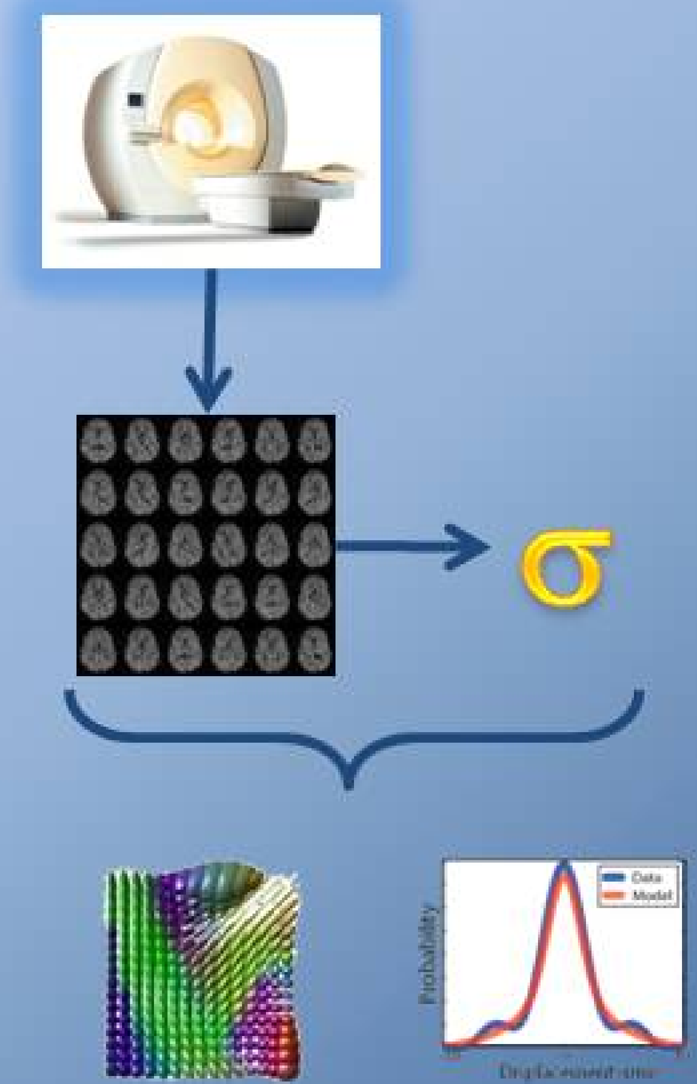


Robust Estimator (Likelihood)



Overview

- **Background**
- Signal and Noise in DW-MRI
- Diffusion Tensor Imaging
- Q-Space Imaging
- Conclusion
- Future Directions



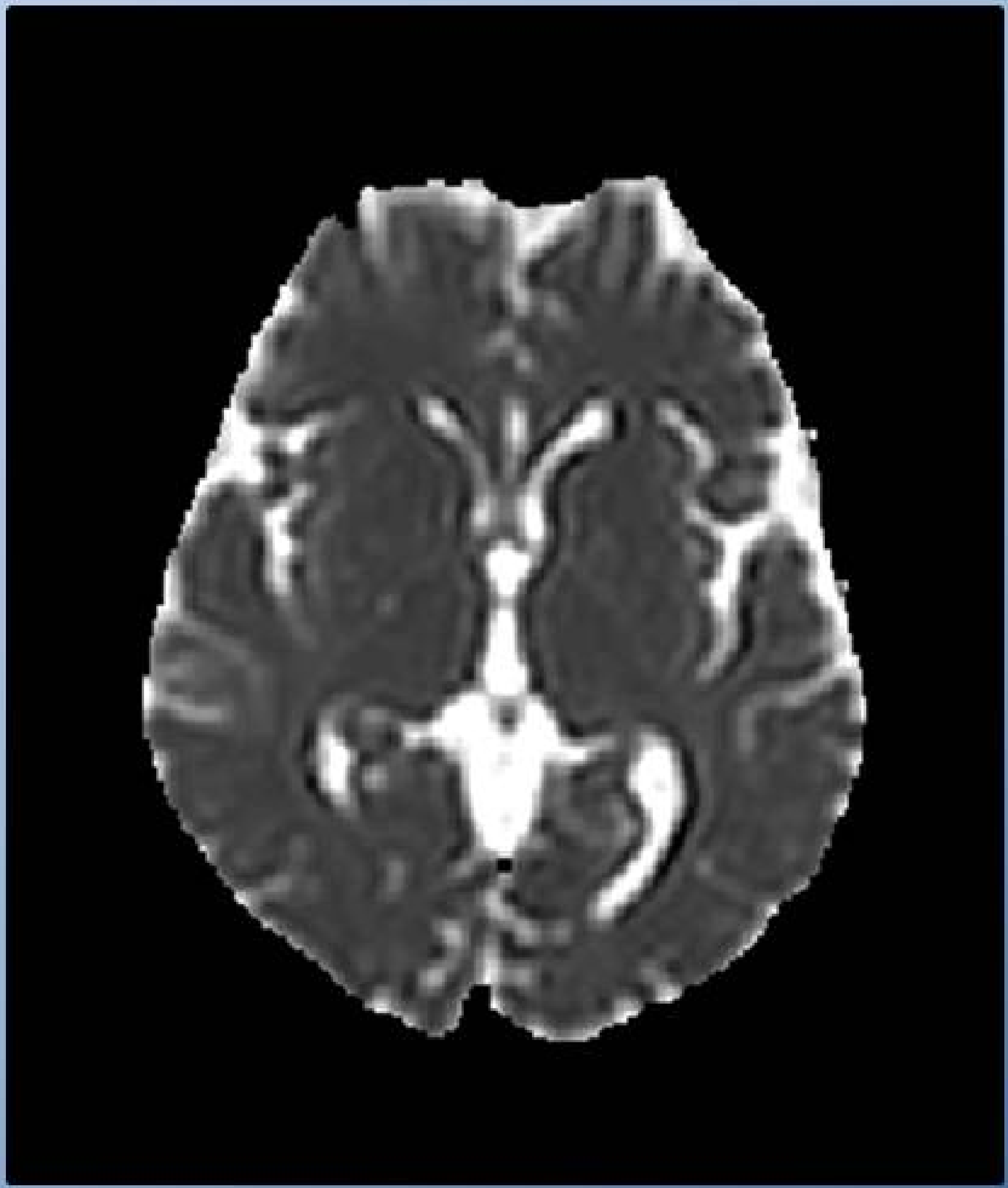
Structural MRI

- **Contrast dominated by**
  - NMR properties
  - T1, T2, PD
- **White matter appears relatively homogeneous**

Diffusion Weighted MRI

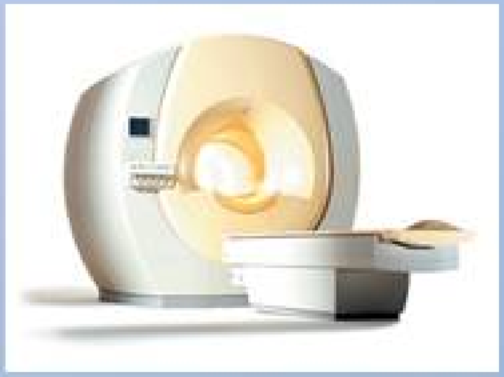
- **Does water diffuse?**
  - Depends on tissue
  - Greatest diffusion in cerebrospinal fluid
- **Mean diffusivity is nearly constant**

Diffusivity

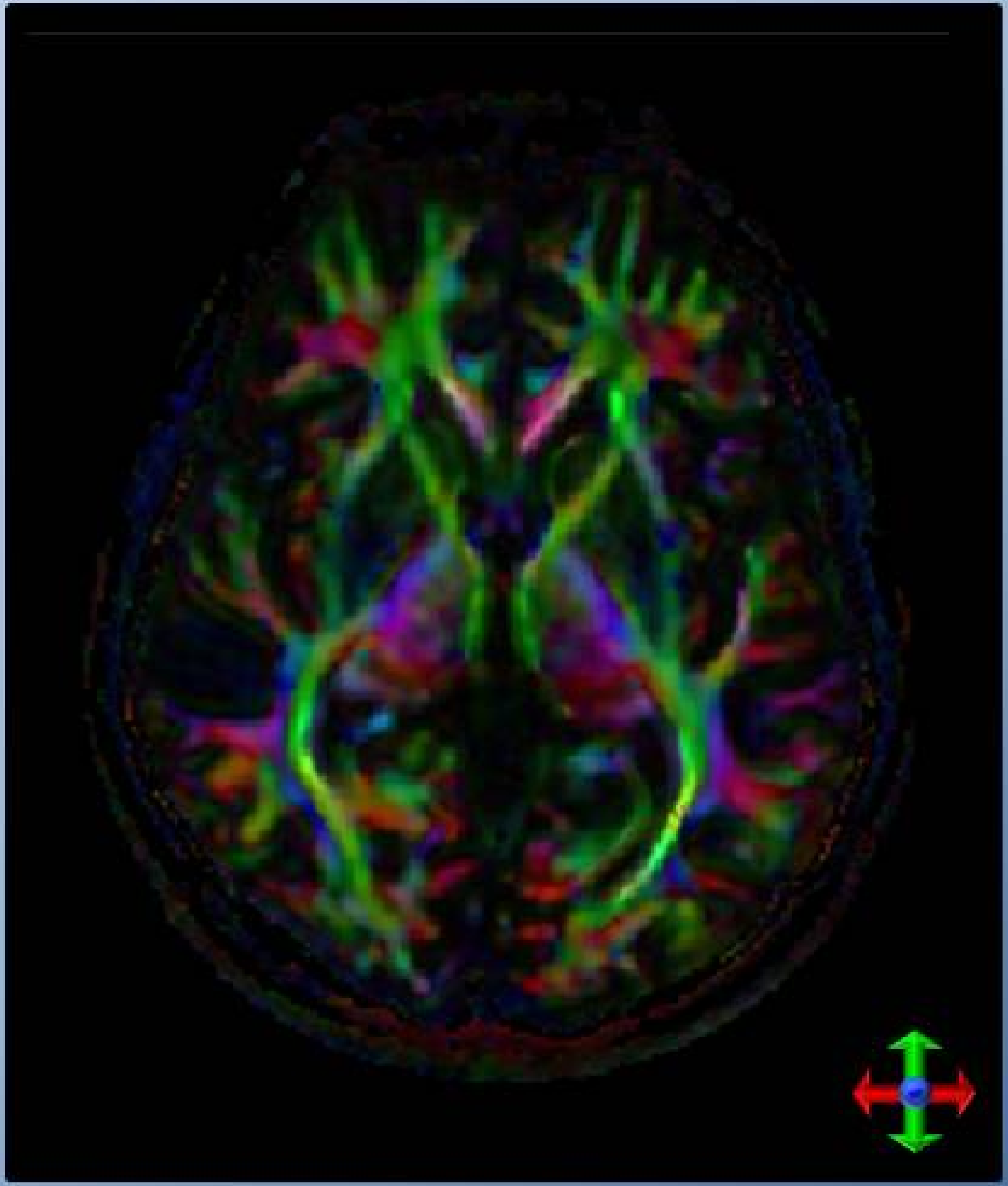


Directional Diffusion

- **Preferred direction?**
  - Diffusivity
  - Orientation
  - Anisotropy…
- **Derived Quantities**



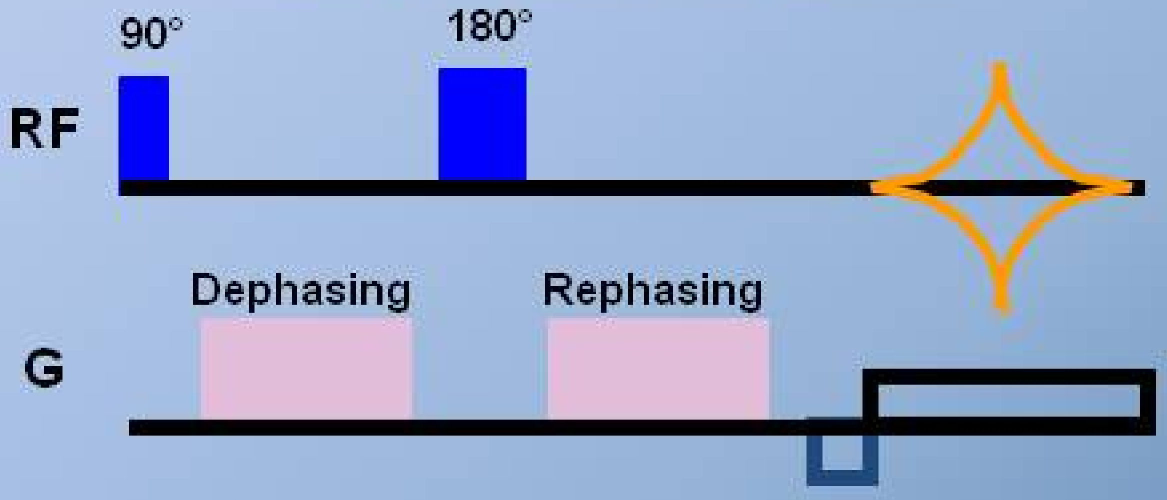
Diffusion Orientation

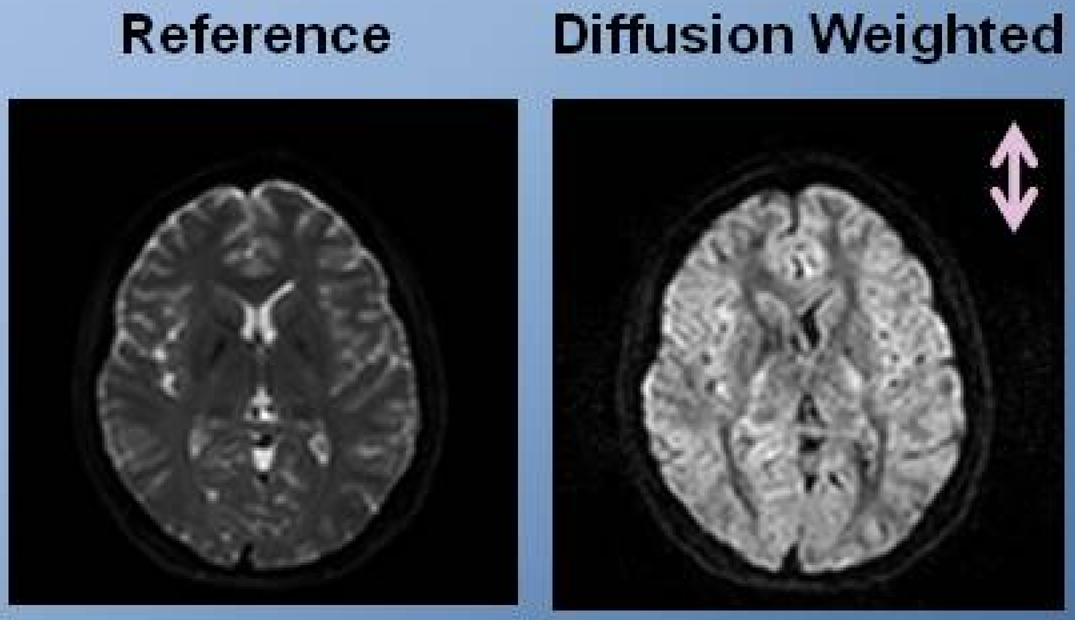


Measuring Diffusion

- **Sensitize to diffusion with balanced gradient pulses**
  - No Motion → No Effect
  - Bulk (Coherent) Motion → Phase Shift
  - **Diffusion (Incoherent) Motion → Signal Loss**

MRI Spin Echo Acqusition





Accounting for Signal Loss

Cory & Garroway 1990

$$S(\mathbf{q}, \mathbf{\Delta}) = S_0 \left| \int_{\mathbf{r}_0}\int_{\mathbf{r}} \rho(\mathbf{r}) \mathbf{P}(\mathbf{r}|\mathbf{r}_0, \mathbf{\Delta}) \times \exp\left[j2\pi\mathbf{q}\cdot(\mathbf{r}-\mathbf{r}_0)\right] \right|$$

- $\mathbf{q}$: Weighting Factor
- $\mathbf{\Delta}$: Diffusion Time
- S_0: Ref.
- $\int\int$: Sum over Volume and Motion
- $\rho(\mathbf{r})$: Number of Spins
- $\mathbf{P}(\mathbf{r}|\mathbf{r}_0, \mathbf{\Delta})$: **Motion Probability "Propagator"**
- $\exp\left[j2\pi\mathbf{q}\cdot(\mathbf{r}-\mathbf{r}_0)\right]$: Phase change due to motion from $\mathbf{r}$ to $\mathbf{r}_0$

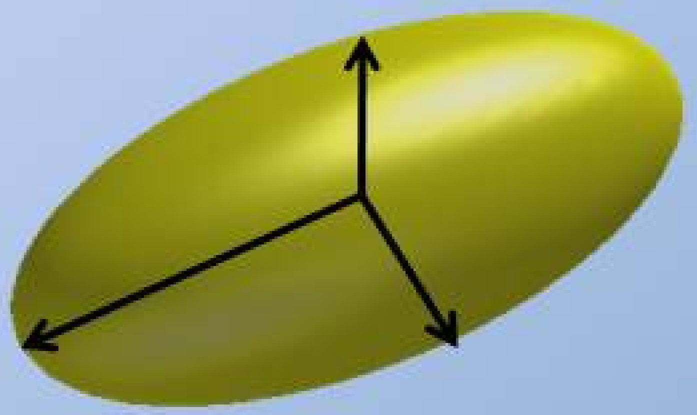
Note (units: 1/length):

$$\mathbf{q} = \frac{1}{2\pi}\gamma\mathbf{g}\delta$$

Motion Probability Propagators

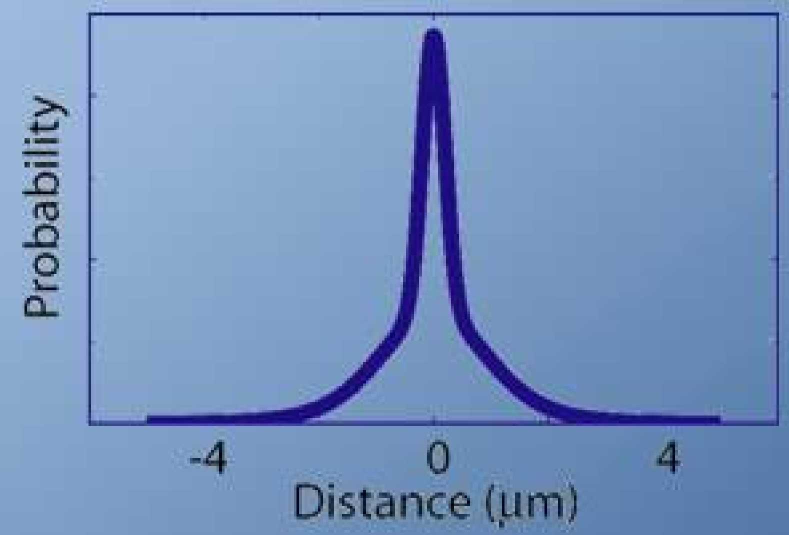
Diffusion Tensor MRI

- 3-D Gaussian
  - *Diffusion by direction*
    - Integrity and connectivity
    - Tensor ellipsoids



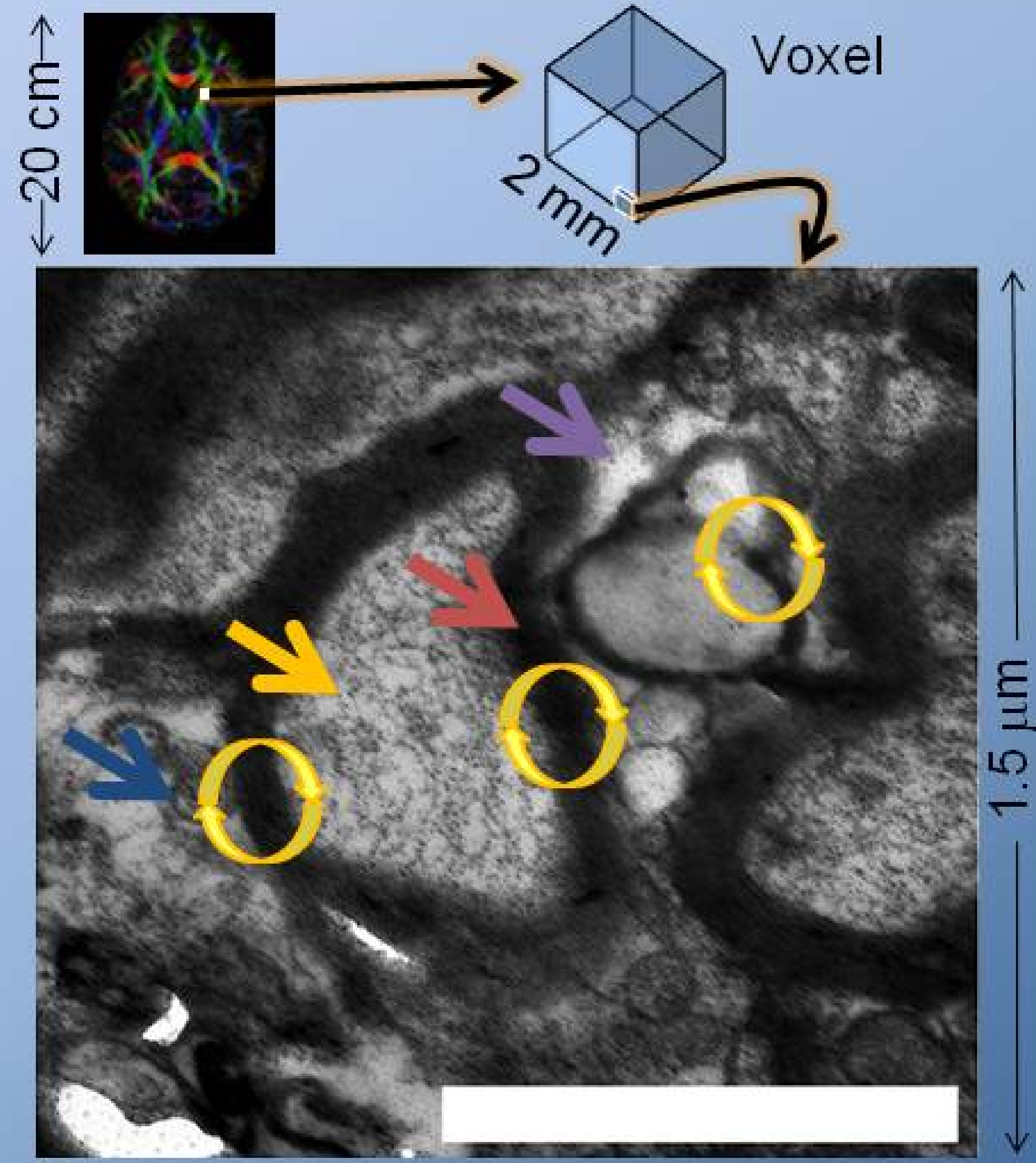
Q-Space MRI

- 1-D Nonparametric
  - *Diffusion by displacement*
    - Restriction environment
    - Probability density functions



Where Does the Signal Come from?

- **Sources of signal**
  - Intra-axonal
  - Myelin
  - Extra-cellular
  - Intra-glia
- **All of the above!**
  - Apprx. 5.2×10^{20} water protons/voxel
- And **exchange**!



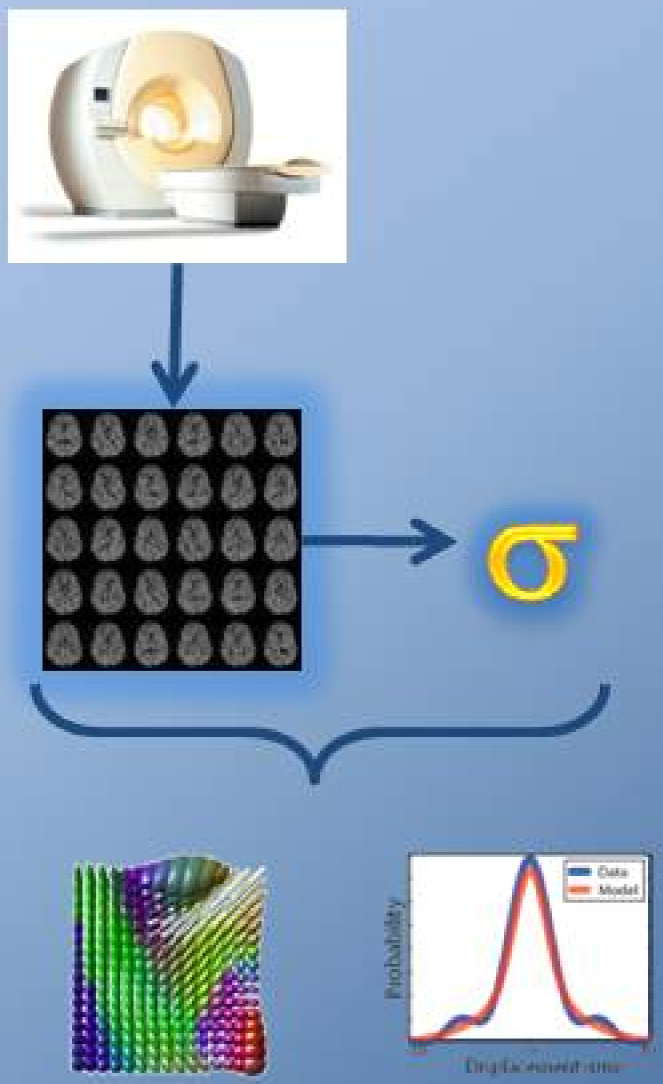
Likelihood in DW-MRI

$$\mathcal{L}(\text{observations}; \text{acquisition}, \text{propagator})$$

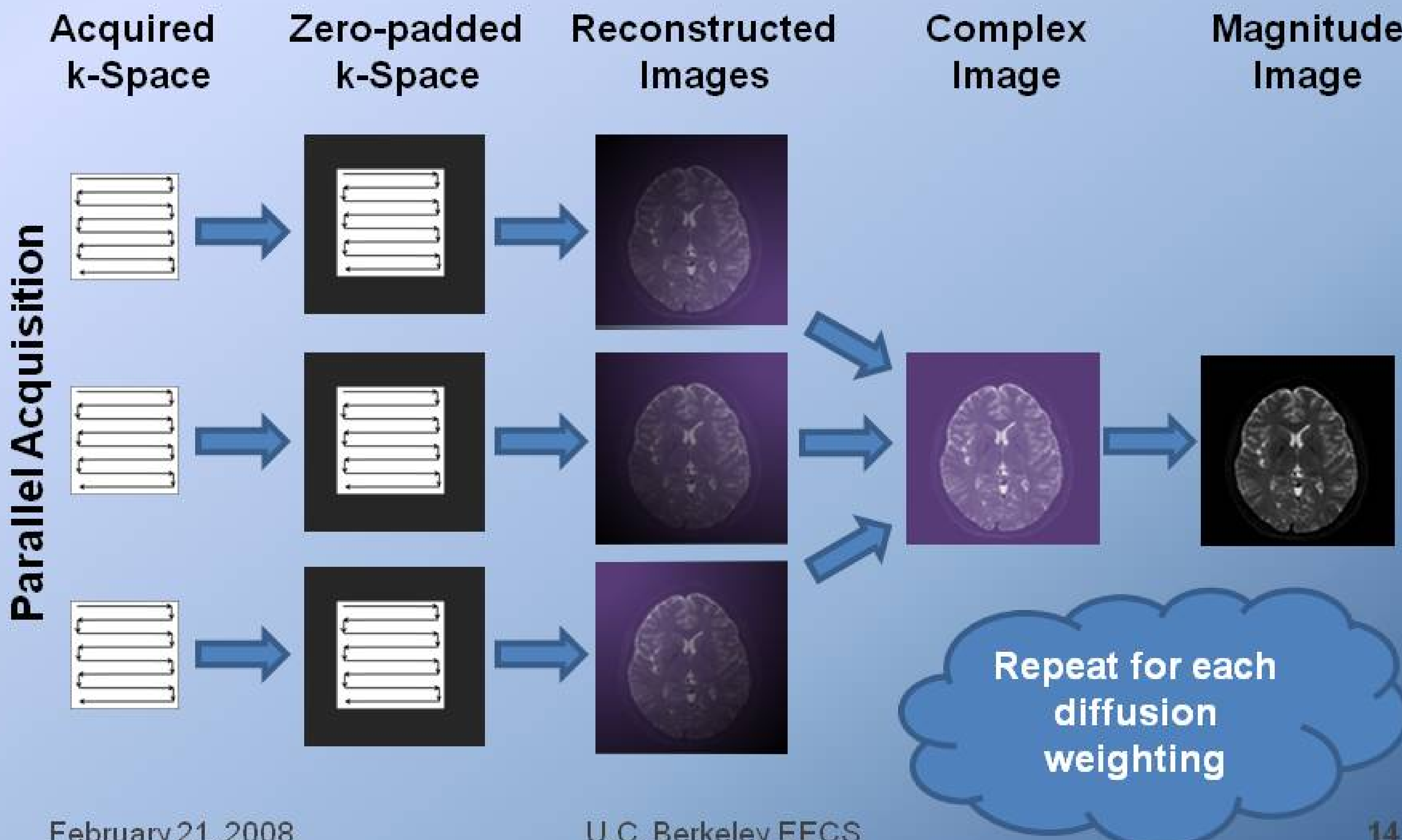
- Explain and account for diffusion behavior of water protons *in vivo*
  - Understand the acquisition (signal theory)
  - Model diffusion propagator

Overview

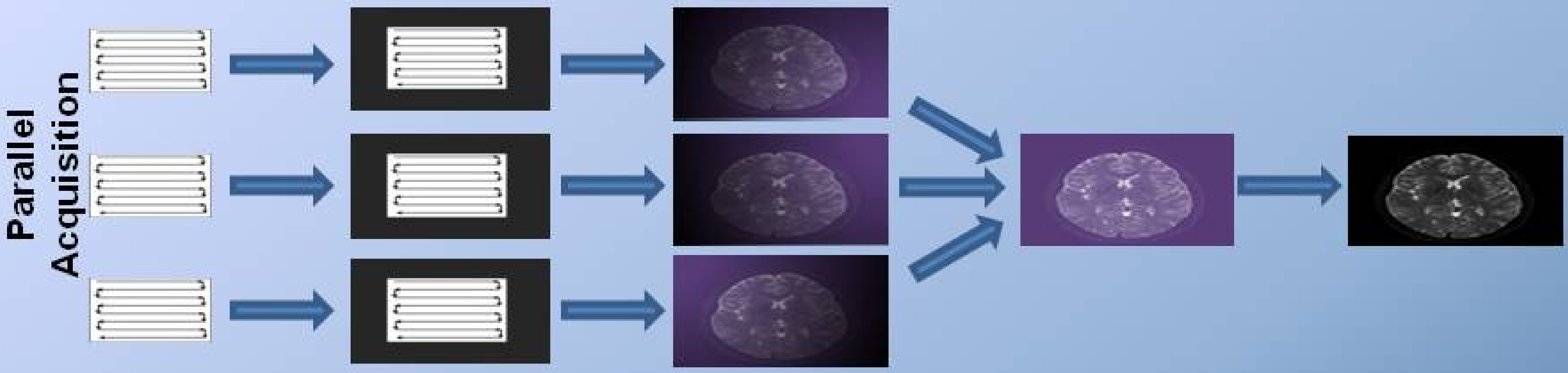
- Background
- **Signal and Noise in DW-MRI**
- Diffusion Tensor Imaging
- Q-Space Imaging
- Conclusion
- Future Directions



Inside the Scanner



Noise Propagation



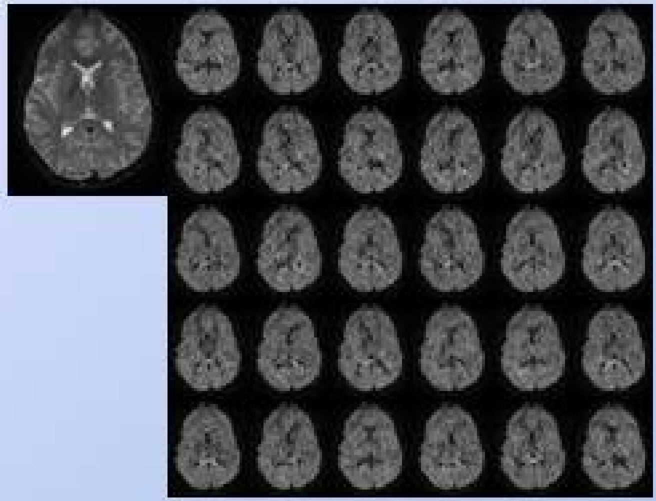
Acquired k-Space	Zero-padded k-Space	Reconstructed Images	Complex Image	Magnitude Image
i.i.d.	i.i.d. (central)	Spatially Correlated	Spatially Correlated	Spatially Correlated
$\mathcal{N}(0,\sigma^2)+ j\mathcal{N}(0,\sigma^2)$	$\mathcal{N}(0,\sigma^2)+ j\mathcal{N}(0,\sigma^2)$	$\mathcal{N}(0,\sigma^2)+ j\mathcal{N}(0,\sigma^2)$	$\mathcal{N}(0,\sigma_{xy}^2)+ j\mathcal{N}(0,\sigma_{xy}^2)$	$\mathcal{R}(S_{xy},\sigma_{xy})$

Artifacts!

$$\mathcal{R}(S_{xy},\sigma_{xy})+F_{xy}$$

Outside the Scanner

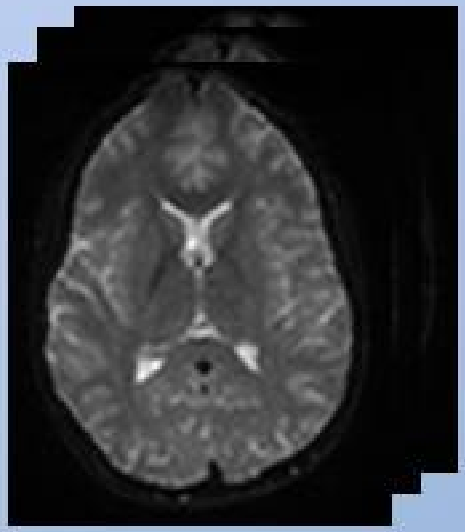
Acquired Data



Diffusion Images i.i.d.
Spatially Correlated

$$\mathcal{R}(S_{gxy}, \sigma_{xy}) + F_{xy}$$

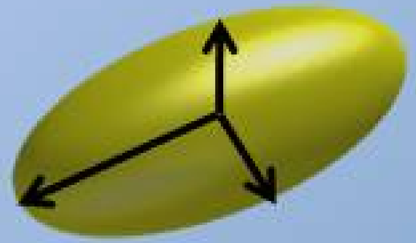
Motion Corrected

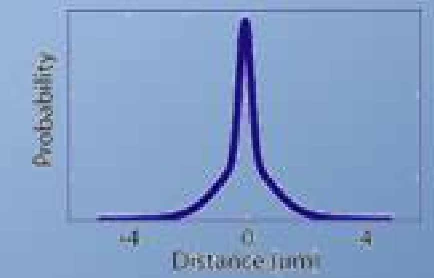


Diffusion Images i.i.d.
Spatially Correlated

$$\mathcal{R}(S_{gxy}, \sigma_{xy}) + \tilde{F}_{xy}$$

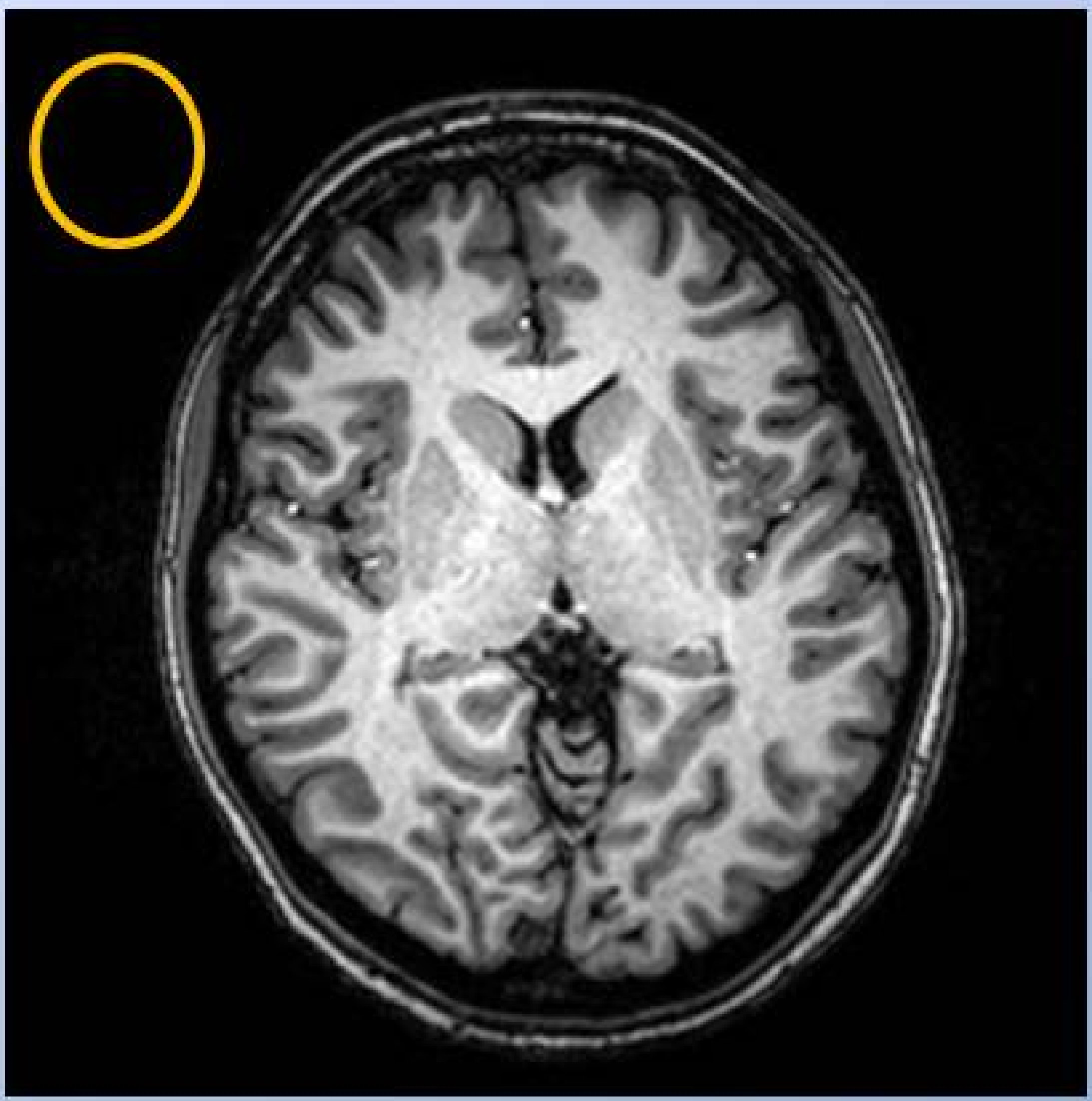
Diffusion Model





Traditional Noise Estimation

Kaufman et al. 1989



Traditional Method

- Select a background region
- Rician → Rayleigh in absence of signal

Challenges

- **Spatially varying noise**
  - Parallel imaging
- Correlated noise
  - Up-sampling
- Non-representative background
  - Ghosting artifacts
  - Background suppression
- Limited time available for clinical sequences

Robust Noise Estimation

Landman et al. 2007a,2008b

Scan 1

$\mathcal{R}(S_{gxy}, \sigma_{xy})$

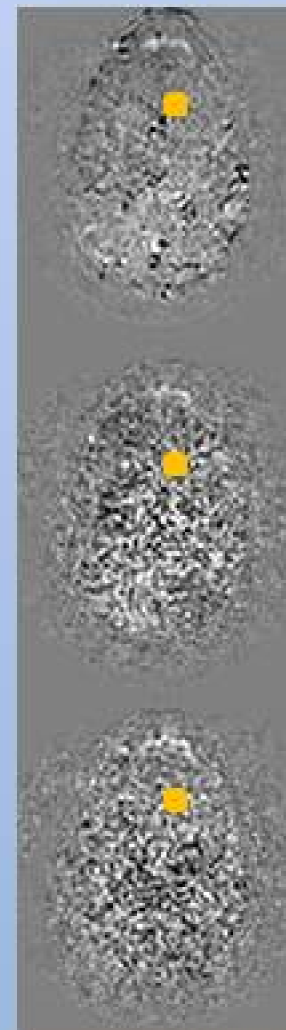
-

Scan 2

$\mathcal{R}(S_{gxy}, \sigma_{xy})$

=

Difference



$\sim \mathcal{N}(0, 2\sigma_{xy}^2)$

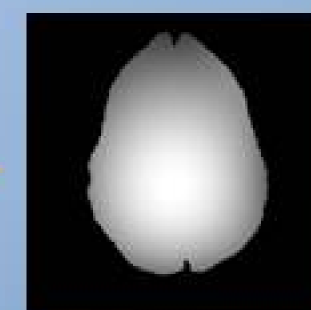
$S_{gxy} > 3\sigma_{xy}$

Q_n scale estimator

Local Noise Estimate

$\sim \mathcal{N}(\sigma_{xy}, \frac{\sigma_{xy}^2}{2N})$

Regularized Noise Estimate



Chebyshev polynomial fit (2D-3rd degree) using high intensity voxels

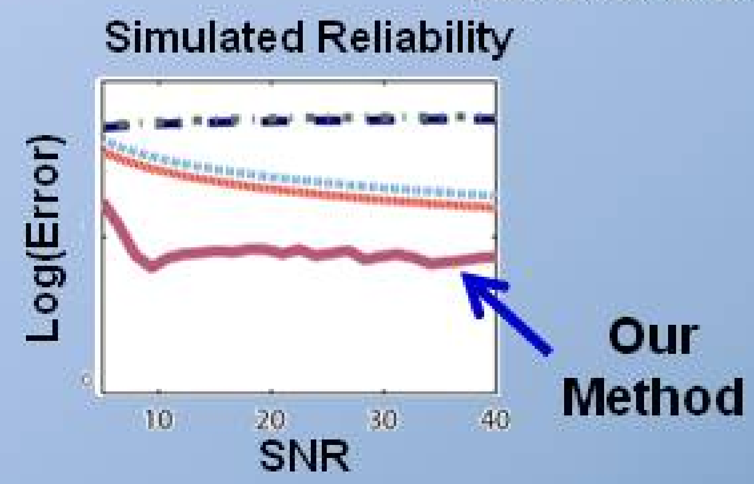
How Can We Validate?

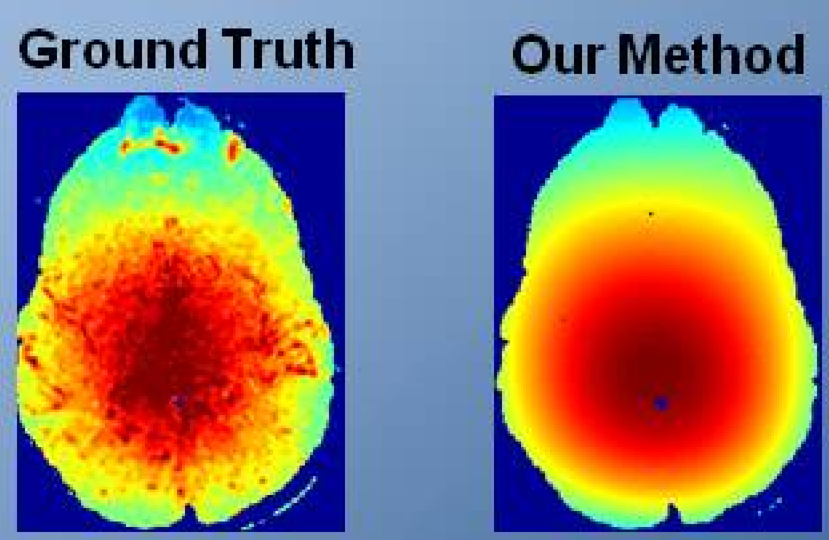
- **Map Noise Field vs. Traditional Scalar Methods**
  - Compare median field estimate
- **Simulation**
  - What is the predicted accuracy?
- **Phantom**
  - How does noise level correlate with the number of signal averages?
- ***In vivo***
  - How do estimates based on clinical data compare to ground truth noise levels?

Validation

- **Simulation**
  - 100x more accurate when accounting for spatially variable noise and artifacts
- **Phantom**
  - In agreement with theory: R^2=0.99
  - Other methods: $R^2 \leq 0.95$
- ***In vivo***
  - Spatially consistent with ground truth estimates (~5%)
  - Mean estimate within 1.7±0.9%
  - Other methods: ≥11.2±1.9%

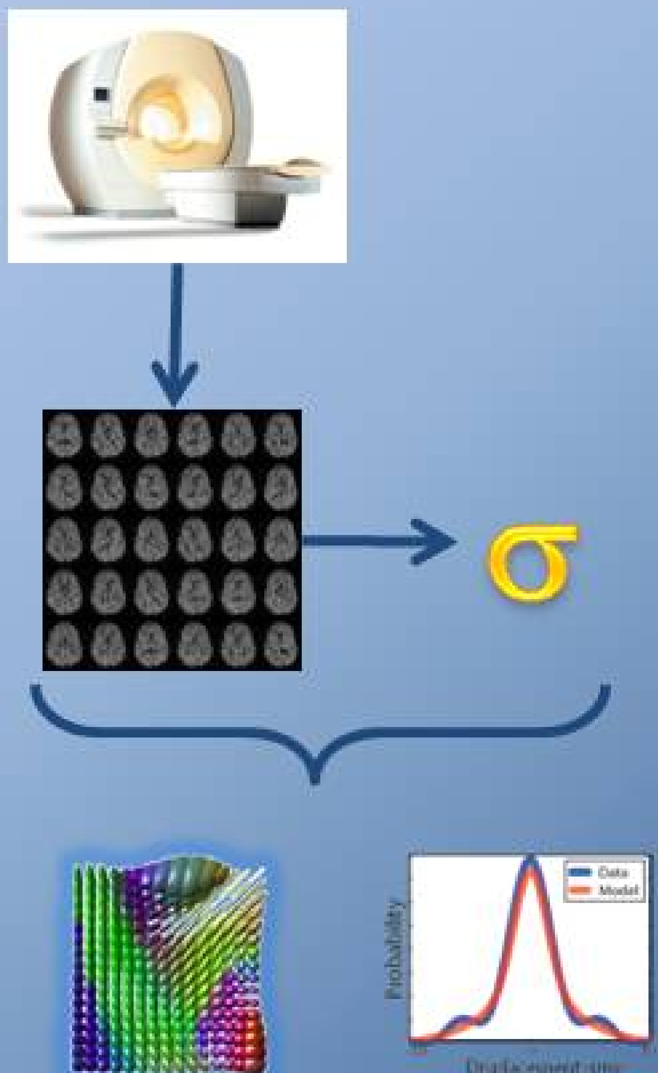
Landman et al. 2008b





Overview

- Background
- Signal and Noise in DW-MRI
- **Diffusion Tensor Imaging**
- Q-Space Imaging
- Conclusion
- Future Directions



Stejskal-Tanner Tensor Model

Stejskal & Tanner 1965

Signal Attenuation

$$S(\mathbf{q}, \boldsymbol{\Delta}) = S_0 \left| \iint \rho(\mathbf{r_0}) \mathbf{P}(\mathbf{r_0} | \mathbf{r}, \boldsymbol{\Delta}) \times \exp\left[j 2\pi \mathbf{q} \cdot (\mathbf{r} - \mathbf{r_0})\right] \right|$$

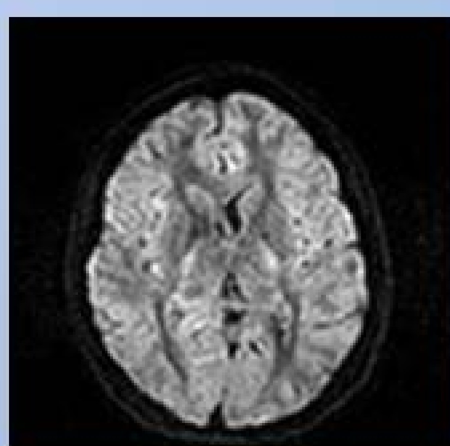
3D Gaussian Propagator

b-value: $b = |\mathbf{q}|^2 \boldsymbol{\Delta}$

Gradient orientation

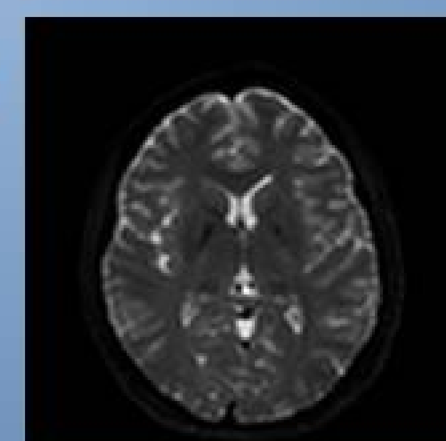
Diffusion tensor

$$S(b, \mathbf{g}) = S_{\text{ref}} e^{-b \mathbf{g}^T \mathbf{D} \mathbf{g}}$$



Signal **with** diffusion weighting

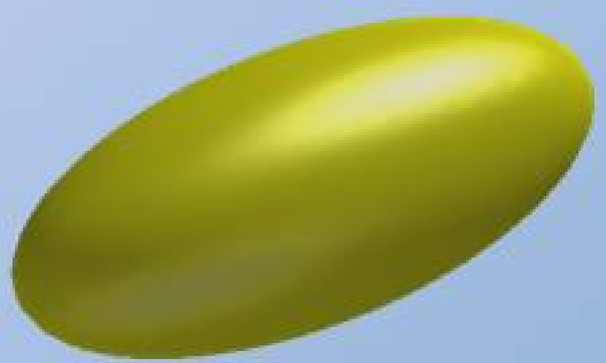
Signal **without** diffusion weighting



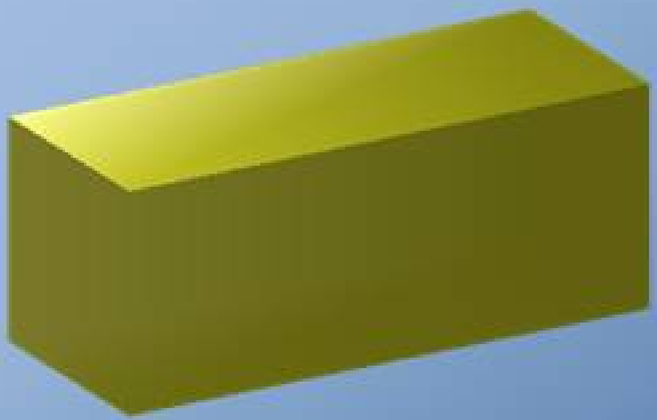
Visualizing Tensors

$$D = \begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{bmatrix}$$

Diffusion Peanut
Distance from the origin represents apparent diffusivity in each orientation



Diffusion Ellipsoid
Surface is an isosurface of the probability of diffusion

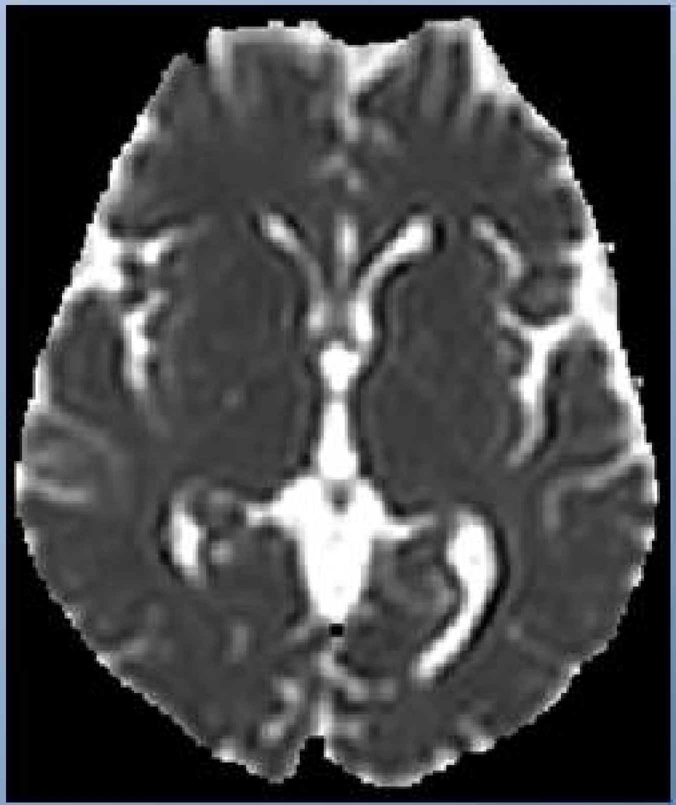


Diffusion Box
Length of edges represents the diffusivity along the principle axes

Diffusivity

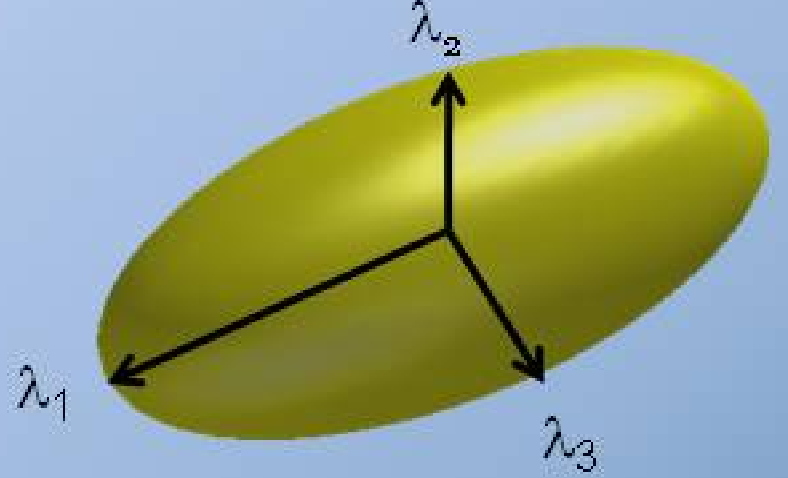
- "Apparent diffusion coefficient" varies by direction: ADC_g
- Need an "invariant" metric
- Solution:
  - Mean diffusivity
  - Apparent diffusion coefficient
  - Tensor trace

$$\mathrm{ADC} = \mathrm{MD} = \frac{\mathrm{tr}\mathbf{D}}{3} = \frac{\lambda_1 + \lambda_2 + \lambda_3}{3}$$



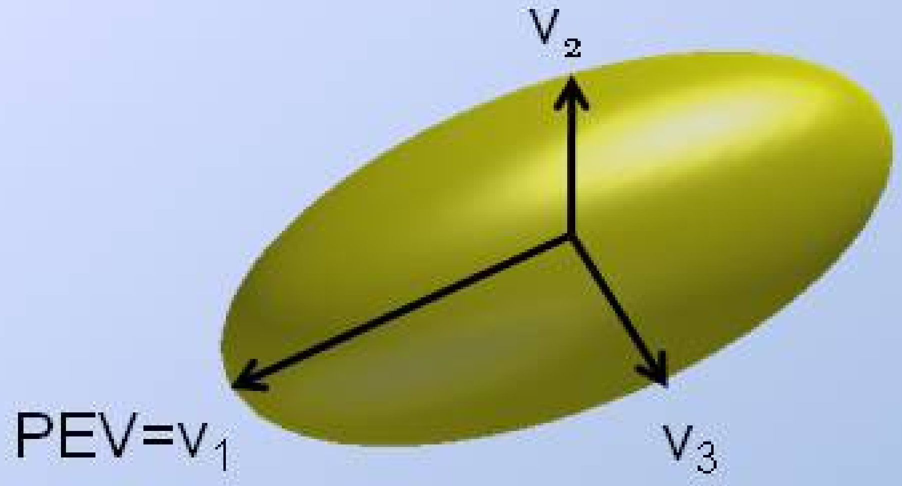
Anisotropy

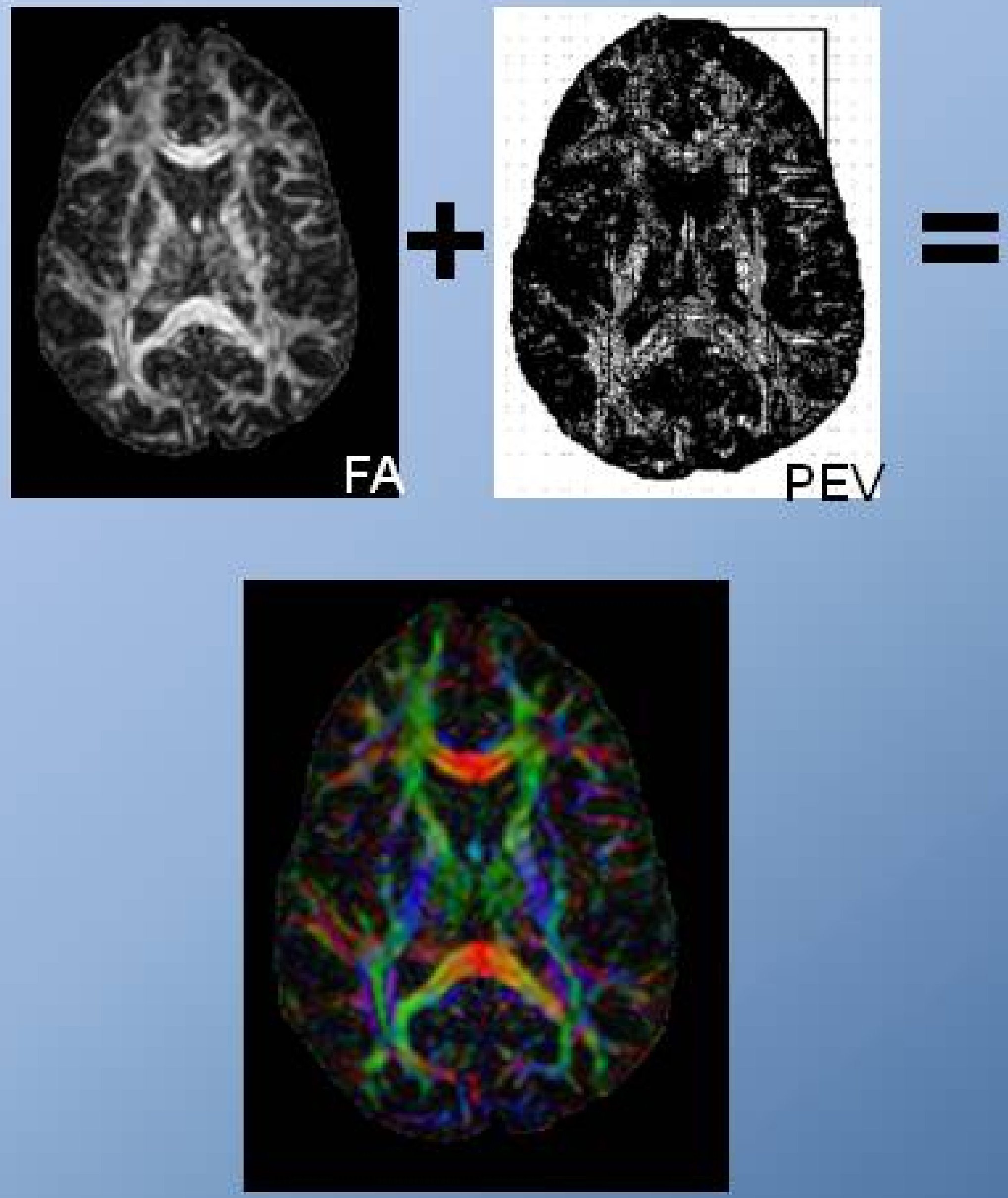
- First Metrics
  - "Ratios" of Eigenvalues
  - Sorting Problem
- Invariant Metrics
  - Relative Anisotropy
  - Lattice Index
  - **Fractional Anisotropy (FA)**



$$\mathrm{FA} = \sqrt{\frac{3}{2}\frac{(\lambda_1-\bar{\lambda})^2+(\lambda_2-\bar{\lambda})^2+(\lambda_3-\bar{\lambda})^2}{\lambda_1^2+\lambda_2^2+\lambda_3^2}}$$

Orientation





<u>Color-coded Diffusion Maps</u>

- Pure red: left to right
- Pure green: front to back
- Pure blue: head to foot
- Colors blended by direction
- Intensity multiplied by FA

Estimating Tensors

Basser & Jones 2002

- Relation of ADC to tensor elements

$$\begin{aligned}\mathrm{ADC}_{\mathbf{g}} &= -\frac{1}{b}\ln\frac{S_{\mathbf{dw}}}{S_{\mathrm{ref}}}\\ &= \mathbf{g}^T\mathbf{D}\mathbf{g}\\ &= [g_x^2\; 2g_xg_y\; 2g_xg_z\; g_y^2\; 2g_yg_z\; g_z^2][D_{xx}\; D_{xy}\; D_{xz}\; D_{yy}\; D_{yz}\; D_{zz}]^T\\ &= \mathbf{G}_{\mathbf{g}}[D_{xx}\; D_{xy}\; D_{xz}\; D_{yy}\; D_{yz}\; D_{zz}]^T\end{aligned}$$

- Least squares (LS) estimate (Gaussian Noise):

$$[\hat{D}_{xx}\; \hat{D}_{xy}\; \hat{D}_{xz}\; D_{yy}\; \hat{D}_{yz}\; \hat{D}_{zz}]^T = [\mathbf{G}^T\mathbf{G}]^{-1}\mathbf{G}^T[\mathrm{ADC}]$$

- Weighted LS (Multivariate Gaussian Noise):

$$[\hat{D}_{xx}\; \hat{D}_{xy}\; \hat{D}_{xz}\; D_{yy}\; \hat{D}_{yz}\; \hat{D}_{zz}]^T = [\mathbf{G}^T\Sigma^{-1}\mathbf{G}]^{-1}\mathbf{G}^T\Sigma^{-1}[\mathrm{ADC}]$$

Challenges

$$-\frac{1}{b}\ln\frac{S_{\mathbf{dw}}}{S_{\text{ref}}} = \mathbf{G}_{\mathbf{g}}[D_{xx}\ D_{xy}\ D_{xz}\ D_{yy}\ D_{yz}\ D_{zz}]^T$$

- **Noise is not Gaussian**
  - Rician distributed observations
  - Bias at low SNR
  - Logarithm of the ratio with common reference
- Spatially varying noise
- Artifacts

A Likelihood Approach

Landman et al. 2007a

$$\frac{S_{\mathrm{dw}}}{S_{\mathrm{ref}}} = e^{-b\mathbf{g}^T\,\mathbf{D}\,\mathbf{g}}$$

Stejskal-Tanner Model

$$S_{\mathrm{ref}} \sim \mathcal{R}(S_{\mathrm{ref}_0}, \sigma_{xy})$$

$$S_{\mathrm{dw}} \sim \mathcal{R}(S_{\mathrm{ref}_0} e^{-b\mathbf{g}^T\,\mathbf{D}\,\mathbf{g}}, \sigma_{xy})$$

Rician Likelihood Model

$$\mathcal{L}(S_{\mathrm{dw}_1} \ldots S_{\mathrm{dw}_n}, S_{\mathrm{ref}}) = \mathcal{R}(S_{\mathrm{ref}}, S_{\mathrm{ref}_0}, \sigma_{xy}) \prod_{i=1}^{N} \mathcal{R}(S_{\mathrm{dw}_i}, S_{\mathrm{ref}_0} e^{-b\mathbf{g_i}^T\,\mathbf{D}\,\mathbf{g_i}}, \sigma_{xy})$$

$$\hat{\mathrm{D}} = \underset{\mathrm{D}, \mathrm{S}_{\mathrm{ref}_0}, \sigma_{\mathrm{xy}}}{\operatorname{argmax}} \mathcal{L}(S_{\mathrm{dw}_1} \ldots S_{\mathrm{dw}_n}, S_{\mathrm{ref}})$$

8 Unknowns

Reference Signal (x 1)

Noise Level (x 1)

Tensor Coefficients (x 6)

Tensor Parameterization

Landman et al. 2007a

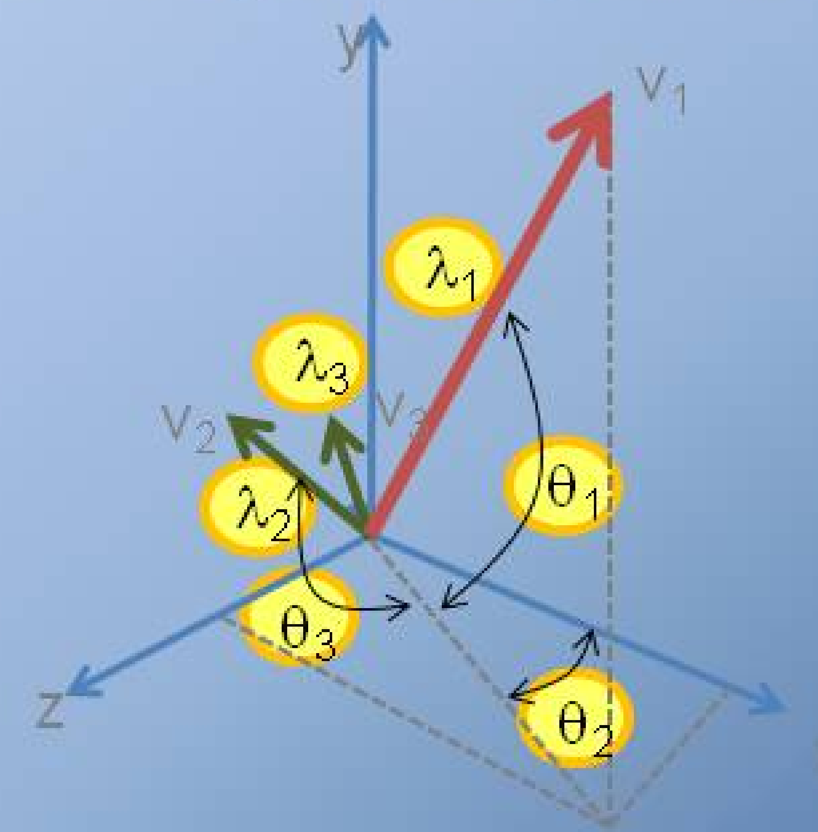
Traditional Approach

$$D = \begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{bmatrix}$$

$$= R^T \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \lambda_3 \end{bmatrix} R$$

$$= \begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \lambda_3 \end{bmatrix} \begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix}^T$$

Euler Angles and Eigenvalues



Proposed Approach

$$= R_{abc} \begin{bmatrix} e^{l_1} & & \\ & e^{l_2} & \\ & & e^{l_3} \end{bmatrix} R_{abc}^T$$

- Rodriguez parameters (a, b, c) based on quaternions
- Eigenvalue Logarithms

Mitigating Artifacts

Landman et al. 2008c

- **Incorrect noise levels**
  - Regularized noise field
    - Bayesian prior probabilities
    - Gaussian prior with mean set to the initial estimate and variance proportional to SNR^2
- **Influence of artifacts**
  - Truncated (Huberized) likelihood function
    - Determine truncation point adaptively from the initial likelihood distribution

$$\hat{\mathrm{D}} = \underset{\mathrm{D},\mathrm{S}_{\mathrm{ref}_0},\sigma_{\mathrm{xy}}}{\operatorname{argmax}} \mathcal{L}(S_{\mathrm{dw}_1} \ldots S_{\mathrm{dw}_n}, S_{\mathrm{ref}})$$

$$\hat{\mathrm{D}} = \underset{\mathrm{D},\mathrm{S}_{\mathrm{ref}},\sigma_{\mathrm{xy}}}{\operatorname{argmax}} \mathcal{L}(S_{\mathrm{dw}_1} \ldots S_{\mathrm{dw}_n}, S_{\mathrm{ref}}) P(\sigma_{xy})$$

$$\hat{\mathrm{D}} = \underset{\mathrm{D},\mathrm{S}_{\mathrm{ref}},\sigma_{\mathrm{xy}}}{\operatorname{argmax}} \mathcal{L}^*(S_{\mathrm{dw}_1} \ldots S_{\mathrm{dw}_n}, S_{\mathrm{ref}}) P(\sigma_{xy})$$

Diffusion Tensor Estimation by Maximizing Rician Likelihood (DTEMRL)

Landman et al. 2007a,2008c

$$\hat{\mathrm{D}} = \underset{\mathrm{D},\mathrm{S}_{\mathrm{ref}},\sigma_{\mathrm{xy}}}{\operatorname{argmax}} \mathcal{L}^*(S_{\mathrm{dw}_1} \ldots S_{\mathrm{dw}_n}, S_{\mathrm{ref}}) P(\sigma_{xy})$$

Initialization

- ☑ Tensor
- ☑ Reference Signal
- ☑ Noise Level
- ☑ Noise Priors

Optimization

Tensor

$$\hat{\mathrm{D}} = \underset{\mathrm{D}}{\operatorname{argmax}} \mathcal{L}^*(\bullet; S_{\mathrm{ref}}; \sigma_{xy}) P(\sigma_{xy})$$

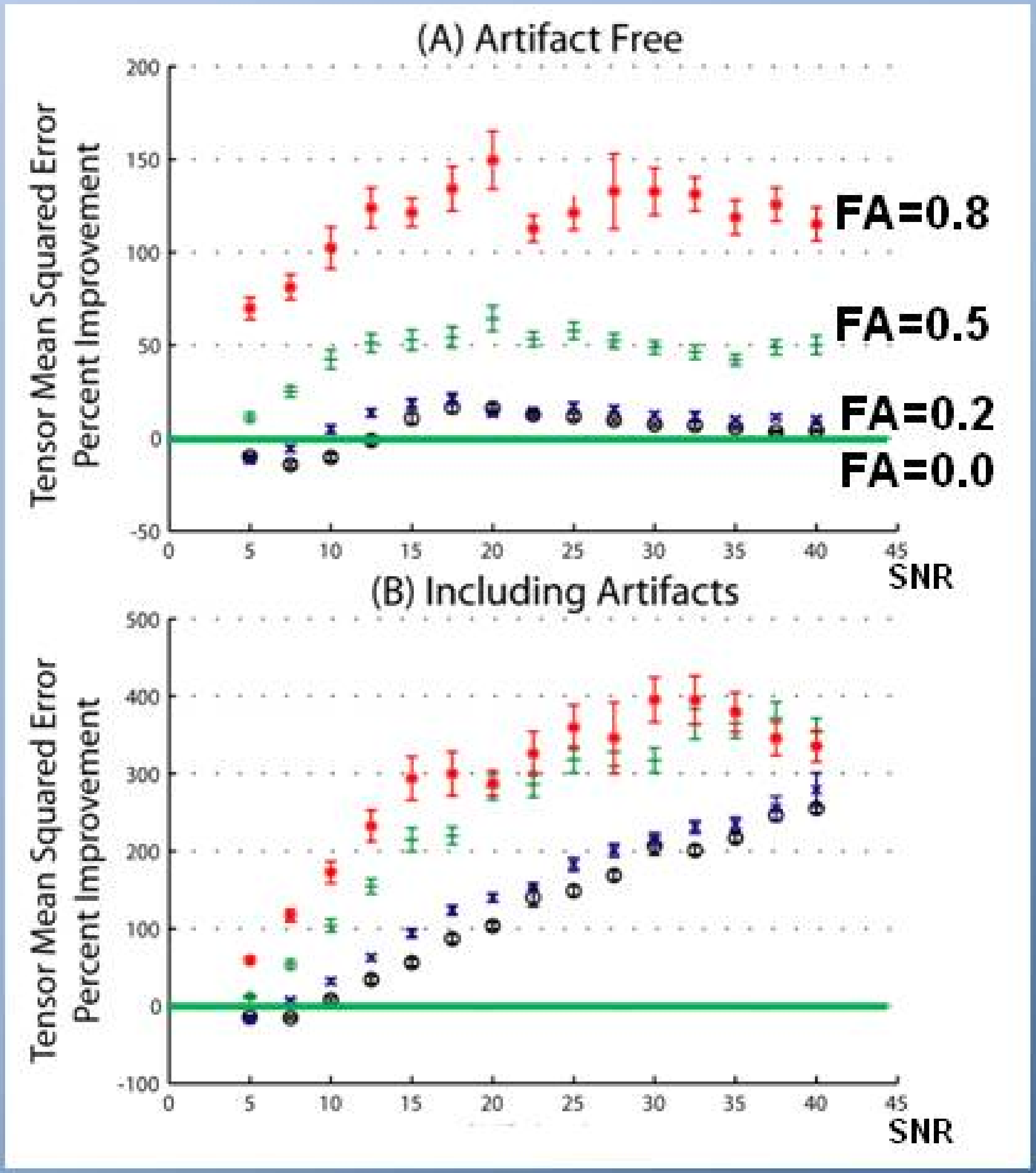
Imaging

$$\{\hat{S}_{\mathrm{ref}}; \hat{\sigma}_{xy}\} = \underset{S_{\mathrm{ref}};\sigma_{xy}}{\operatorname{argmax}} \mathcal{L}^*(\bullet; \hat{\mathrm{D}}) P(\sigma_{xy})$$

Reliability in Simulation

Landman et al. 2008c

- **Idealized (no Artifacts)**
  - Improvements in white matter above 10:1 SNR
  - Little effect on gray matter
- **Realistic (with Artifacts)**
  - Substantial improvements in both white matter and gray matter

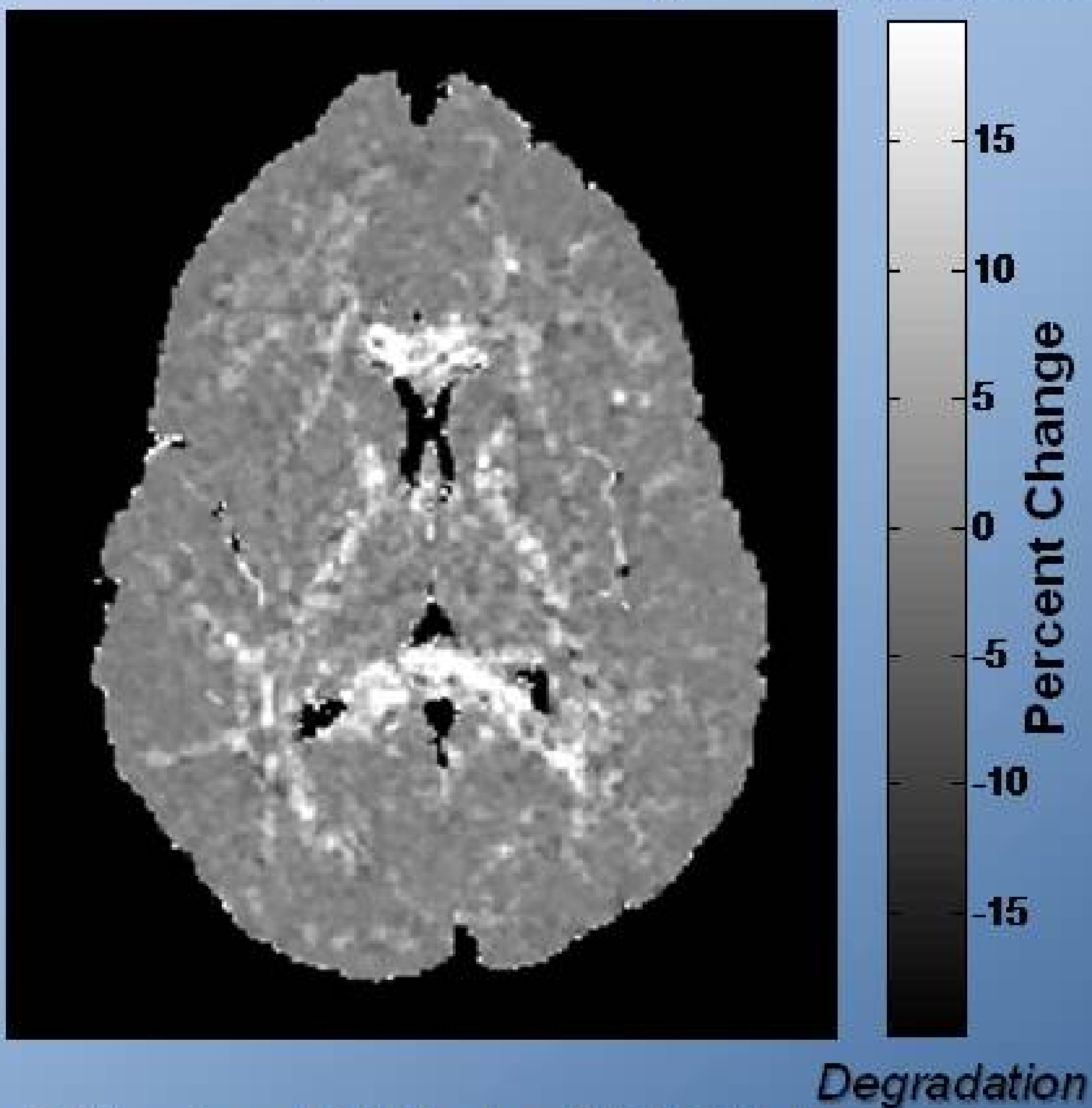


Reliability *In Vivo*

Landman et al. 2007a,2008c

- **Repeated Scanning**
  - One subject scanned 22 times over 3 days
- **Improved reproducibility in white matter**
  - 30%+ tensor coefficients
  - 15%+ FA
- **Little effect in gray matter**

FA Reproducibility

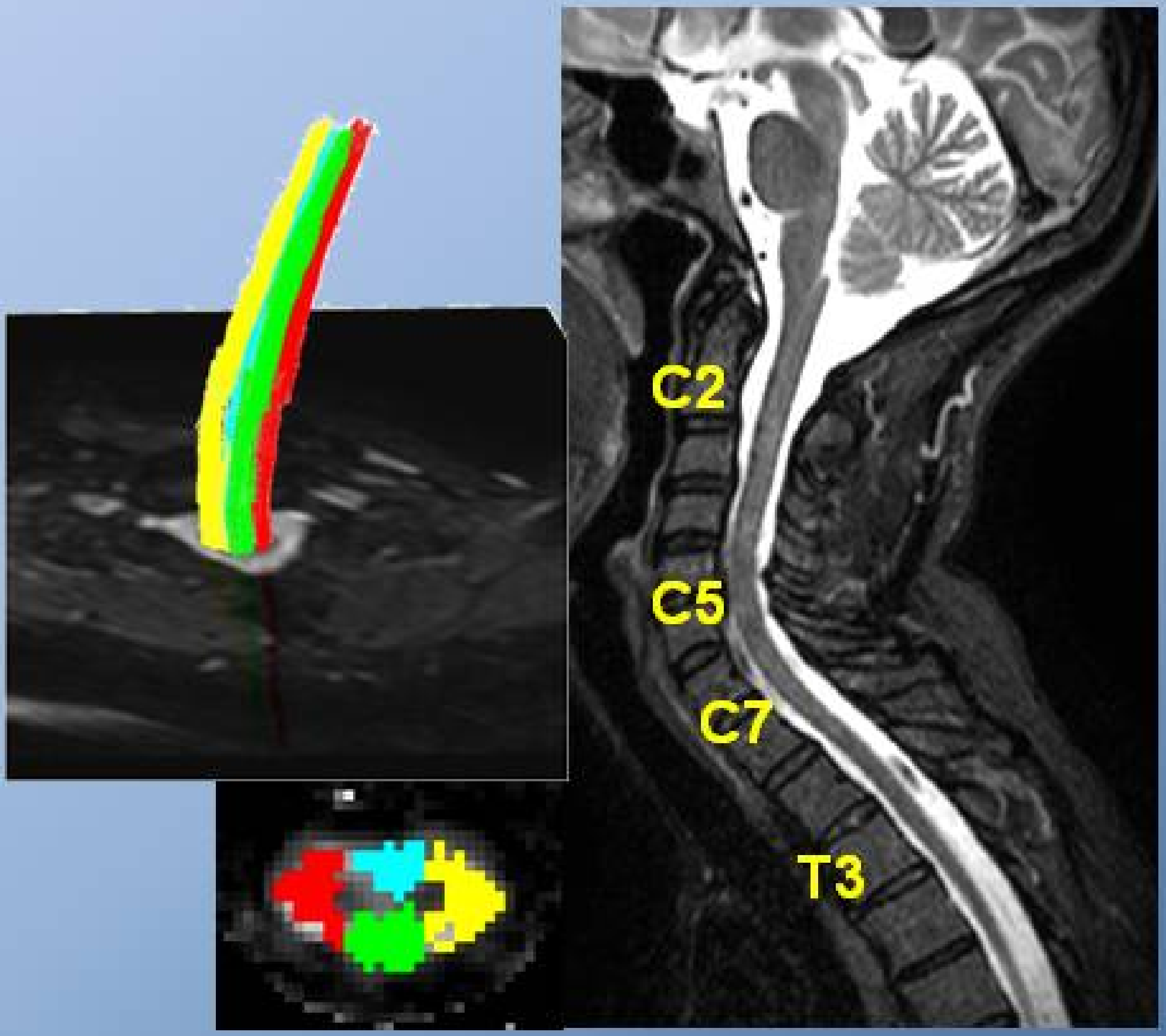


1.5T, b-value of 1000 s/mm^2, 30 DW directions

Spinal Cord DW-MRI

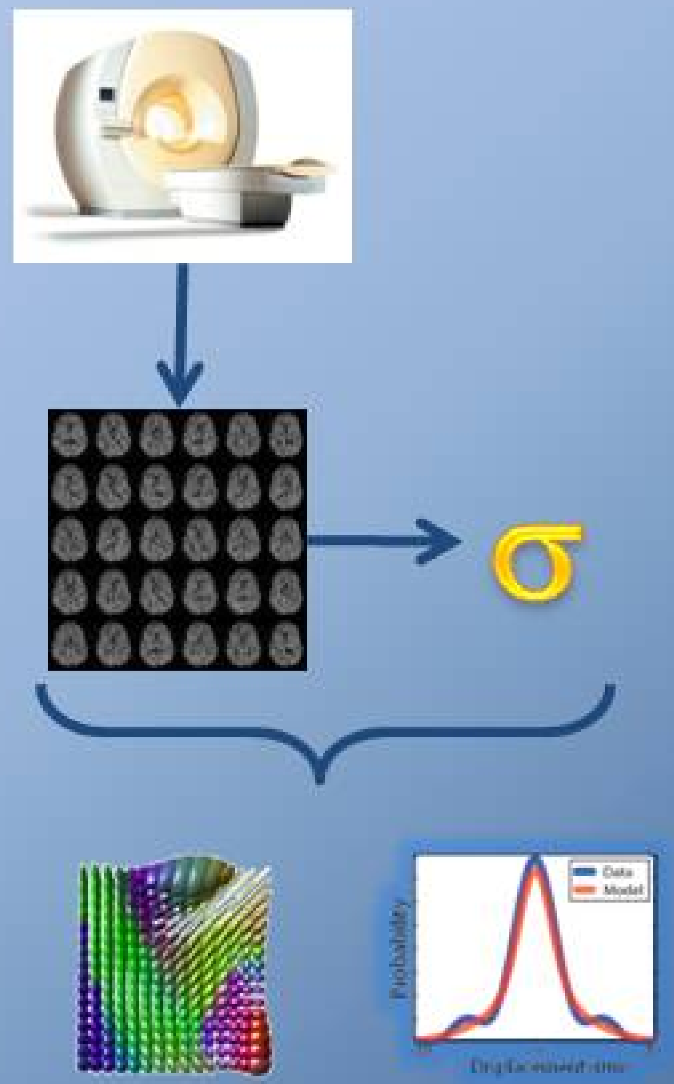
Smith et al. 2008

- **White matter in the spinal cord is highly oriented**
  - Orientation is known
  - Approximately radially symmetric
- **Can we learn more about the cellular environment?**



Overview

- Background
- Signal and Noise in DW-MRI
- Diffusion Tensor Imaging
- **Q-Space Imaging**
- Conclusion
- Future Directions



q-Space Imaging

Signal Attenuation

$$S(\mathbf{q}, \boldsymbol{\Delta}) = S_0 \left| \iint \rho(\mathbf{r_0}) \mathbf{P}(\mathbf{r_0}|\mathbf{r}, \boldsymbol{\Delta}) \times \exp\left[j2\pi \mathbf{q} \cdot (\mathbf{r} - \mathbf{r_0})\right] \right|$$

1D Nonparametric Stationary Propagator

$$S(q, \Delta) = S_0 \left| \int \mathbf{P}(\mathbf{r} - \mathbf{r_0}, \boldsymbol{\Delta}) e^{j2\pi q r} dr \right|$$

- $S(q, \Delta)$: **Observed Signal**
- S_0: **Reference Signal**
- $\mathbf{P}(\mathbf{r} - \mathbf{r_0}, \boldsymbol{\Delta})$: **Propagator**
- $e^{j2\pi q r}$: **Phase**

q-Space Imaging

Signal Attenuation

$$S(\mathbf{q}, \boldsymbol{\Delta}) = S_0 \left| \iint \rho(\mathbf{r_0}) \mathbf{P}(\mathbf{r_0} | \mathbf{r}, \boldsymbol{\Delta}) \times \exp\left[j2\pi \mathbf{q} \cdot (\mathbf{r} - \mathbf{r_0})\right] \right|$$

1D Nonparametric Stationary Propagator

Fourier transform

$$S(q, \Delta) = S_0 \left| \int \mathbf{P}(\mathbf{r} - \mathbf{r_0}, \boldsymbol{\Delta}) e^{j2\pi q r} dr \right|$$

Amplitude Spectrum

- **Estimating the propagator**
  - Iterative reconstruction from amplitude spectrum
  - Assume phase → inverse Fourier transform

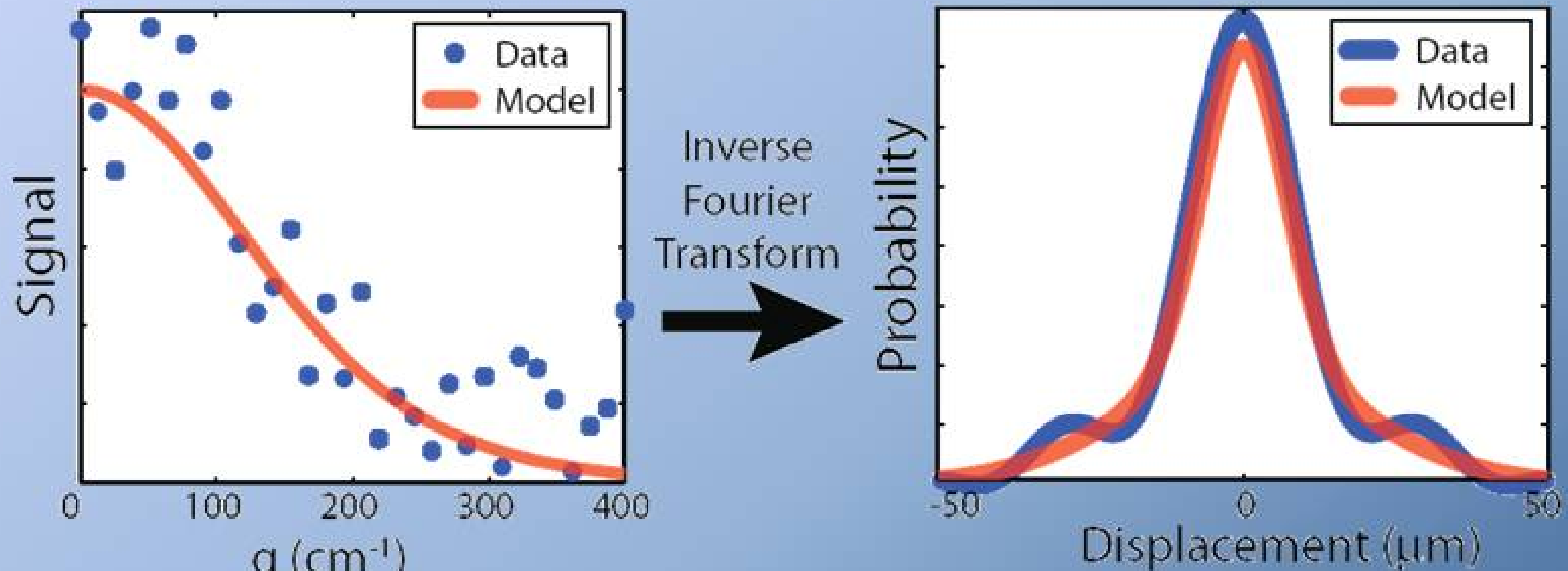
Assumptions

Norris 2001

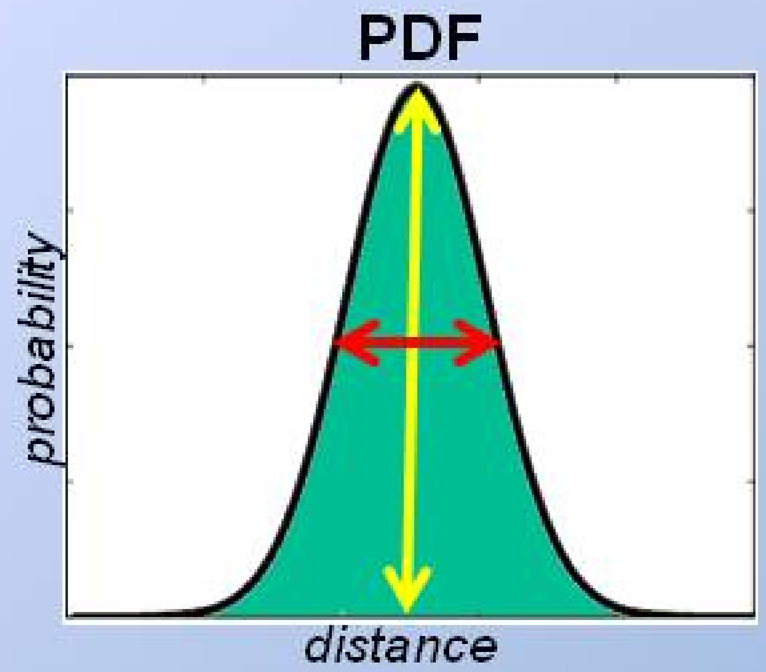
- **"Long-time Limit"**
  - With impermeable membranes and infinite diffusion time, the propagator becomes the autocorrelation of the restriction geometry
  - ➢ Zero Phase
- **In practice for the CNS**
  - Exchange is slow relative (100-600 ms) to diffusion time
  - Diffusion characteristic distances (~10 μm) are greater than the spacing of cellular membranes (1-5 μm)
  - ➢ $\mathbf{P}(\mathbf{r}-\mathbf{r_0},\tau) = S_0^{-1}\int S(q,\tau)e^{-j2\pi qr}dr$

q-Space Experiment

- Acquire $S(q,\Delta)$ at many values of q
- Smooth noisy data
- Take inverse Fourier transform

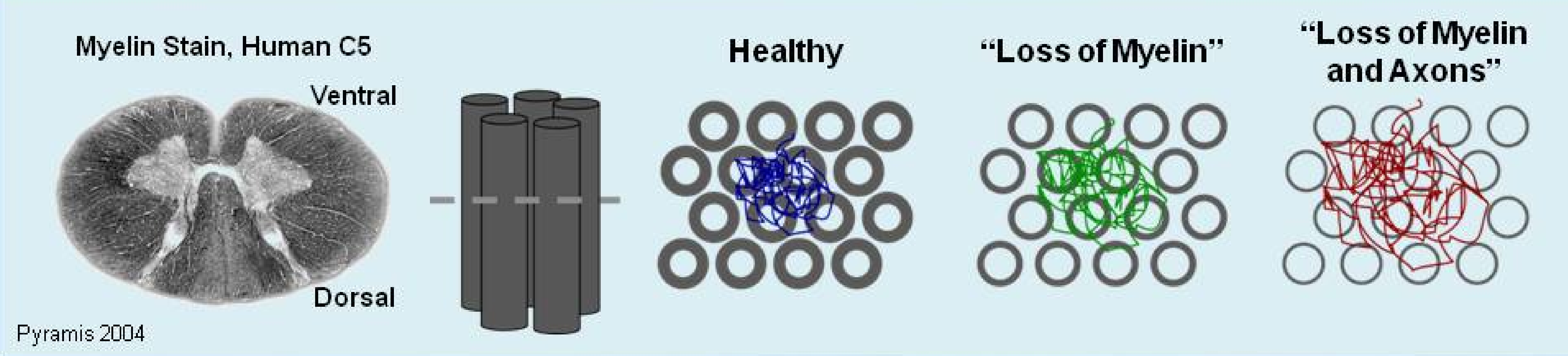


Clinical Contrasts



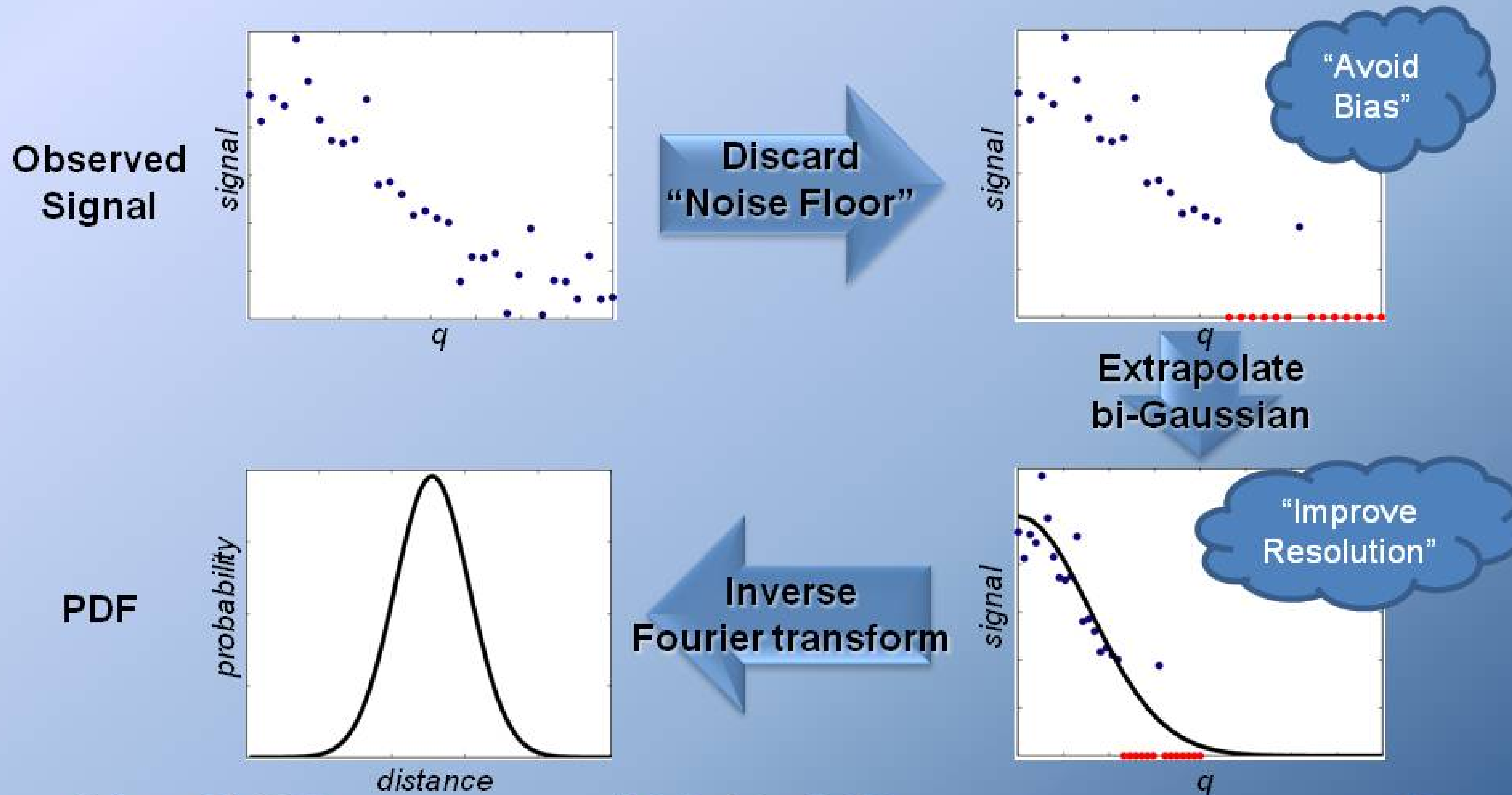
Contrasts

- Mode Probability (**P0**)
- Full Width at Half Maximum (**FWHM**)
- Root Mean Squared Displacement (**RMSD**)



Traditional q-Space Approach

Cohen & Assaf 2002



Challenges

$$S(q,\Delta) = S_0 \left| \int P(r,\Delta) e^{j2\pi qr} dr \right|$$

- **Ad hoc assumptions**
  - "Noise Floor" Criteria
  - Strict Model Fitting
  - Rician distributed observations
  - Bias at low SNR
- Limited acquisition
  - Cannot image *in vivo* at high q
  - Magnitude of spectrum of $P(r,\Delta)$
- Artifacts

A Likelihood Approach

Landman et al. 2008d

- **Properties of diffusion PDF's**
  - Positive } **PDF**
  - Symmetric
  - Monotonic } **Physical constraints**
- **Model**
  - Positive mixture of zero-mean Gaussians
  - Estimate variances
  - Adaptively adjust model complexity
    - Determine number of basis functions with the L-curve criterion

Q-space Estimation by Maximizing Rician Likelihood: QEMRL

Landman et al. 2007a

$$S_{\text{dw}}(q) = S_0 \sum_i f_i e^{-kq^2 D_i}$$

$$\sum_i f_i = 1, \forall f_i \geq 0$$

Mixture Model for Smooth PDF's

$$D \in [3 \times 10^{-5}, 3 \times 10^{-3}] \text{ mm}^2/\text{s}$$

Constrain to Physiological Diffusivities

$$S_{\text{dw}} \sim \mathcal{R}(S_{\text{ref}_0} e^{-kq^2 D}, \sigma_{xy})$$

$$\mathcal{L}(S_{\text{dw}_1} ... S_{\text{dw}_n}, S_0) = \prod_{j=1}^{N} \mathcal{R}(S_{\text{dw}_j}, S_0 \sum_i f_i e^{-kq^2 D_i}, \sigma_{xy})$$

Rician Likelihood

$$\widehat{\{D\}} = \underset{\{D\}, S_0, \sigma_{xy}}{\text{argmax}} \; \mathcal{L}^*(S_{\text{dw}_1} ... S_{\text{dw}_n}, S_0) P(\sigma_{xy})$$

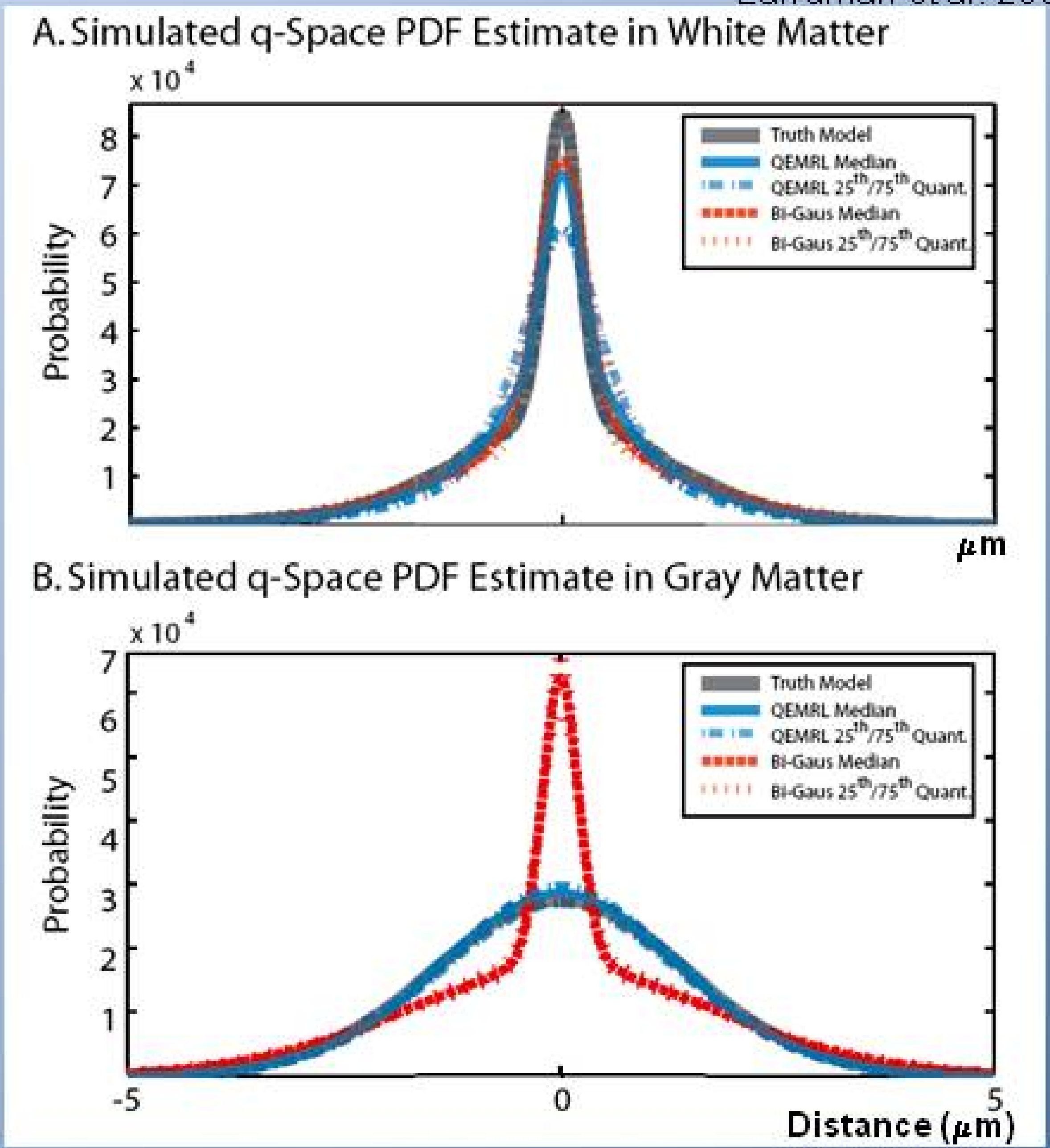
Truncated Likelihood and Bayesian Regularization

L-Curve Criteria to Select Number of Components

Reliability in Simulation

- **Overall:** 95% improvement in integrated MSE of estimated PDF's
- **White matter:** 21% improvement
- **Gray Matter:** 98% improvement

Landman et al. 2008d

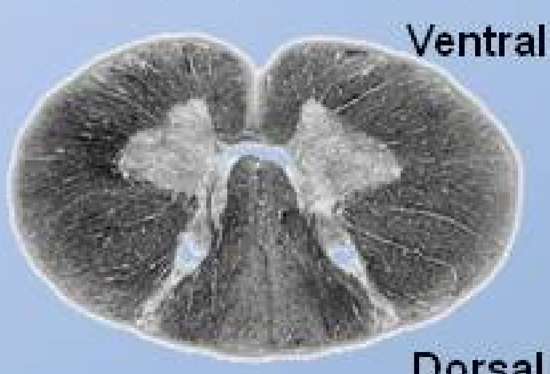


32 samples linearly spanning q=0 to 400 cm^{-1} at an SNR of 7:1

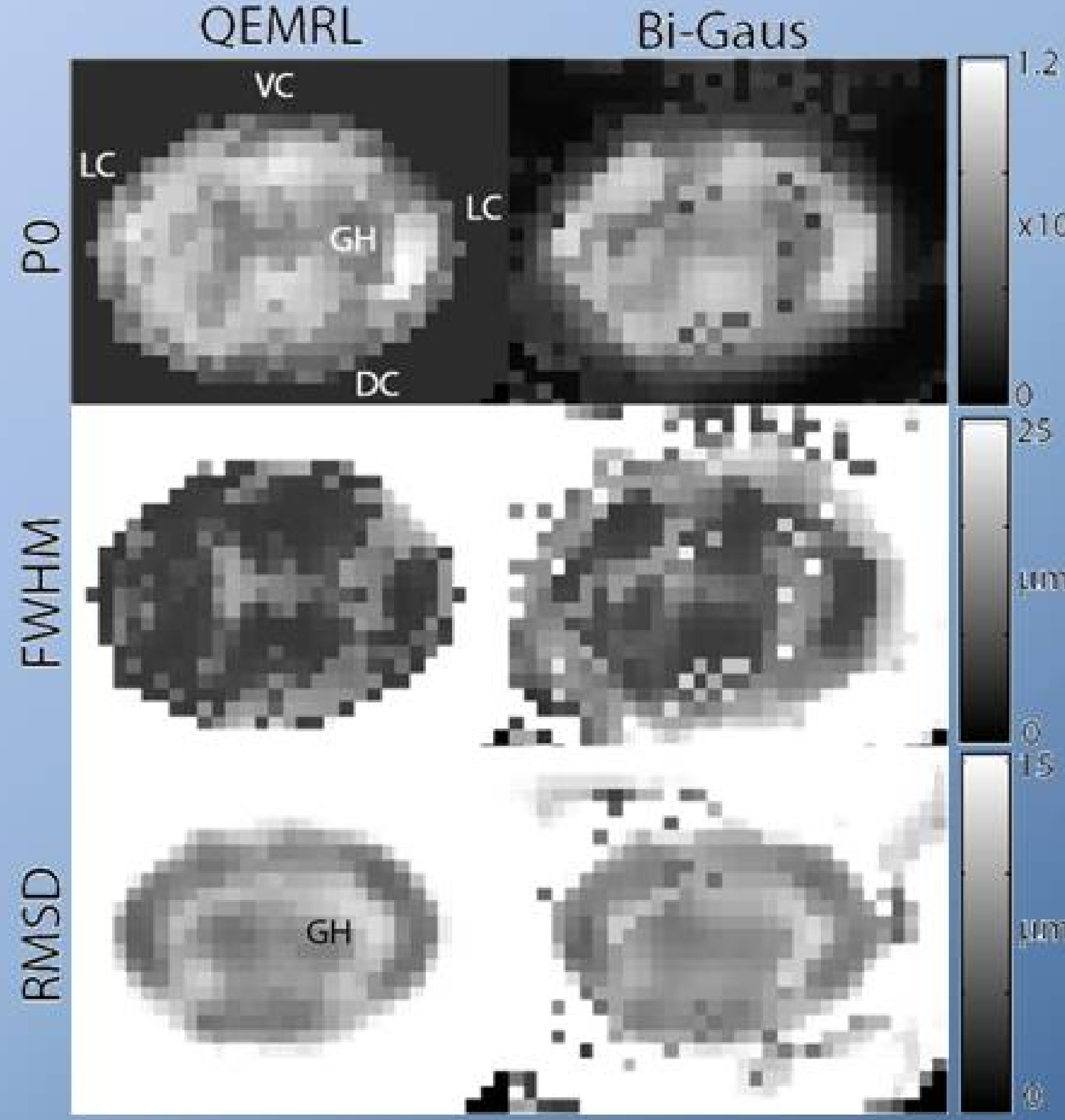
Reliability *In Vivo*

- **Improved reproducibility**
  - Mode Probability (**P0**) : **23%**
  - Full Width Half Maximum (**FWHM**) : **18%**
  - Root Mean Square Displacement (**RMSD**) : **26%**
- **Increased tissue contrast**

Myelin Stain, Human C5

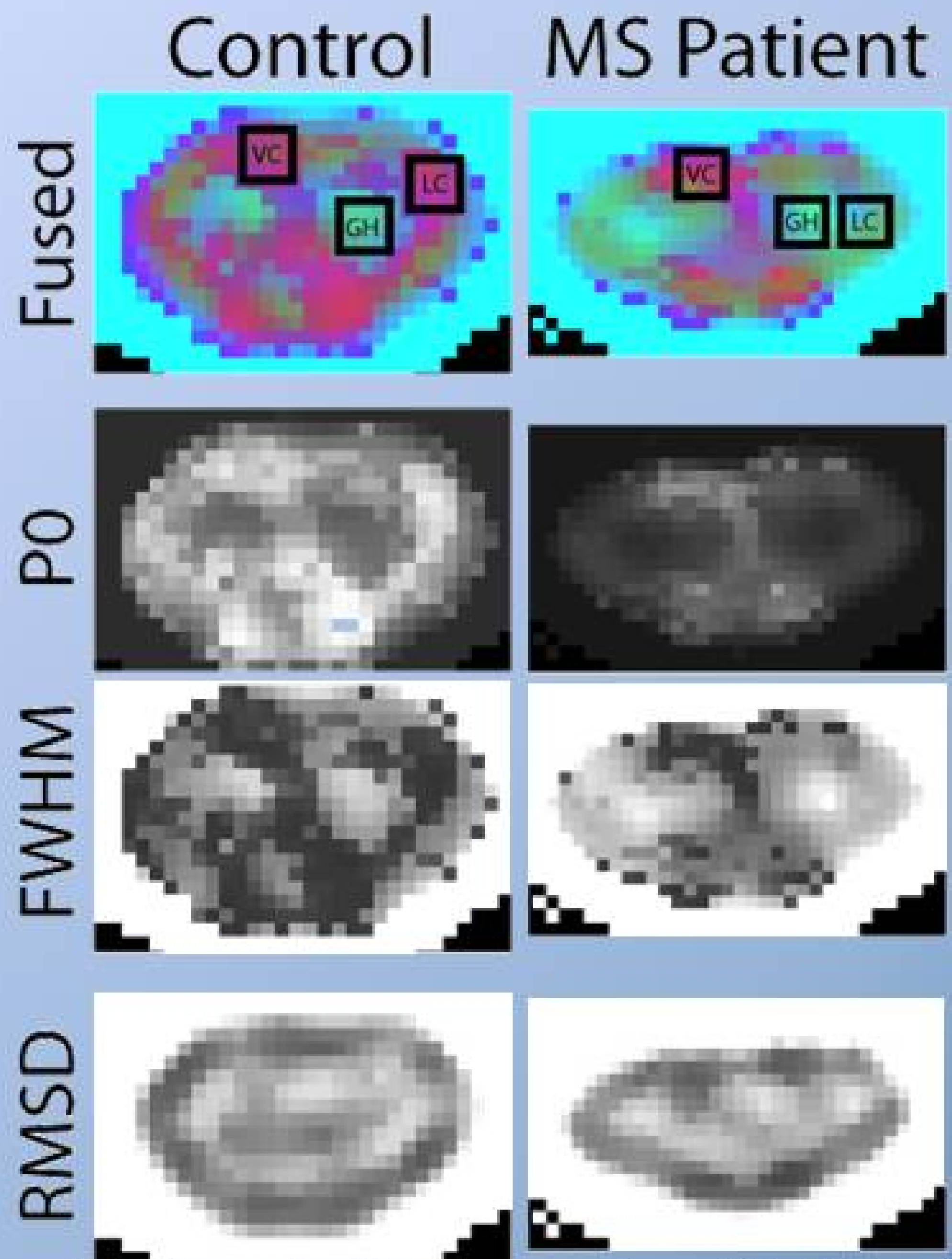


Landman et al. 2008d

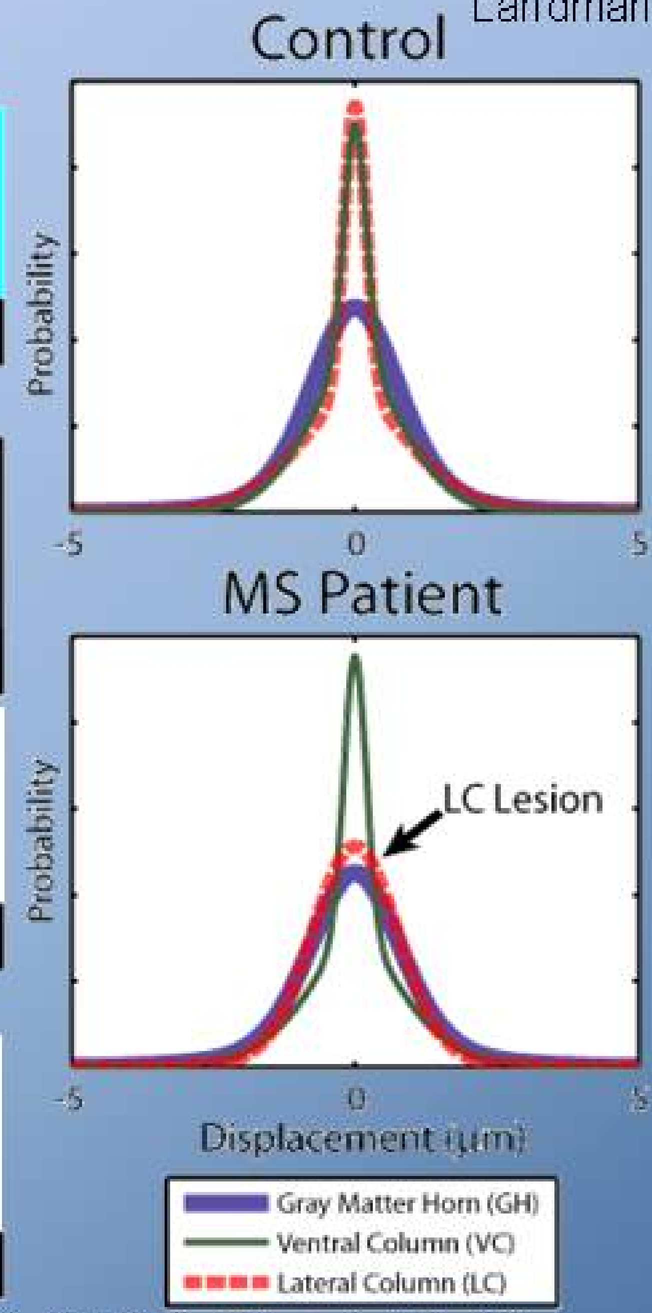


3T, 32 samples linearly spanning q=0 to 414 cm^{-1}
SNR of ~7:1, 1.3x1.3x3.0 m

Potential Biomarkers for Multiple Sclerosis (MS)



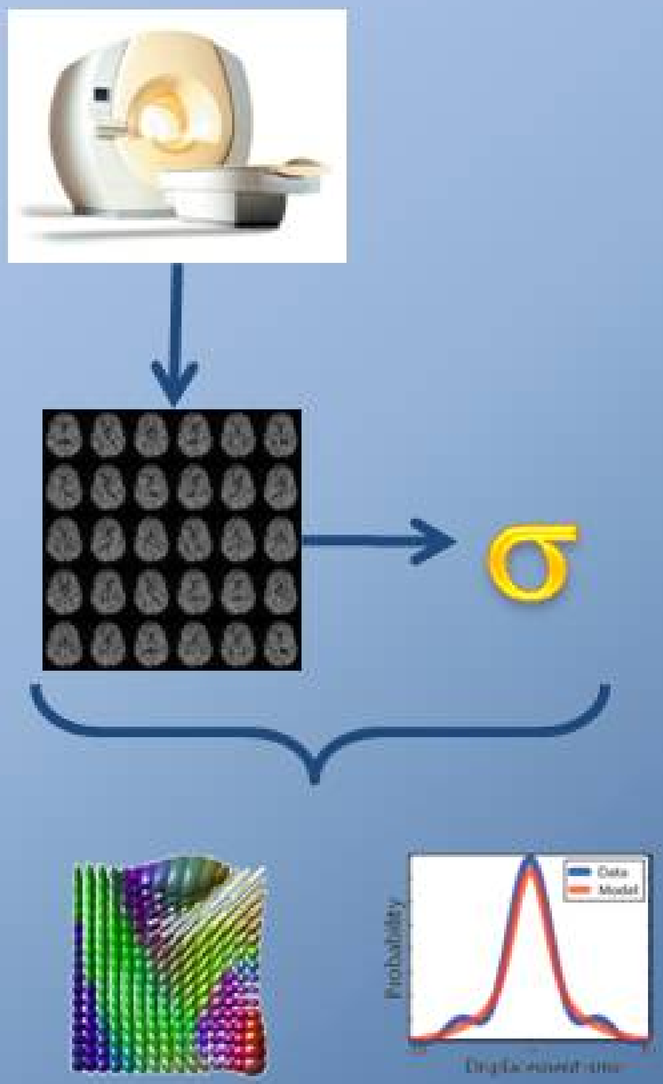
Landman et al. 2008e



3T, 32 samples linearly spanning q=0 to 414 cm^{-1}, SNR of ~7:1, 1.3x1.3x3.0 m

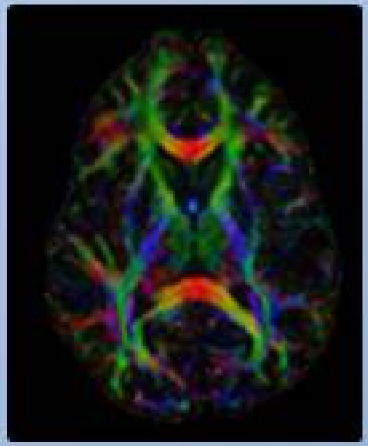
Overview

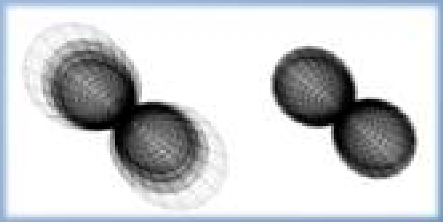
- Background
- Signal and Noise in DW-MRI
- Diffusion Tensor Imaging
- Q-Space Imaging
- **Conclusion**
- Future Directions

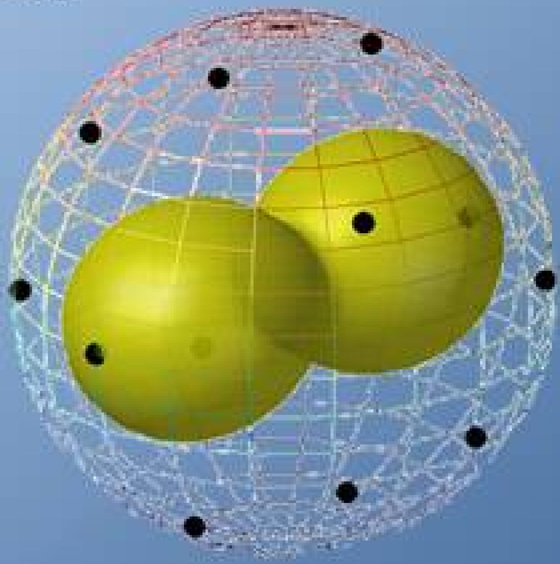


Conclusion

- **DW-MRI reveals cellular structure**
  - Rician noise corrupts analyses
- **Robust likelihood techniques**
  - Properly account for noise
  - Increase tissue contrast
  - Improve reliability
- **Likelihood models have great potential**
  - Forward applications: analysis
  - Reverse problems: acquisition design

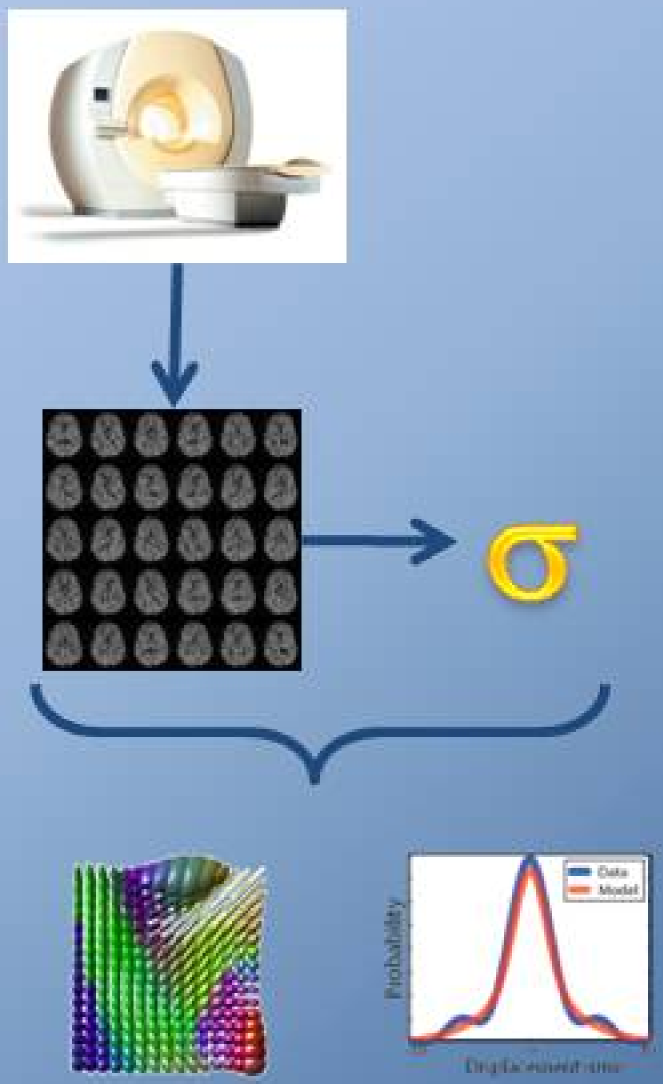






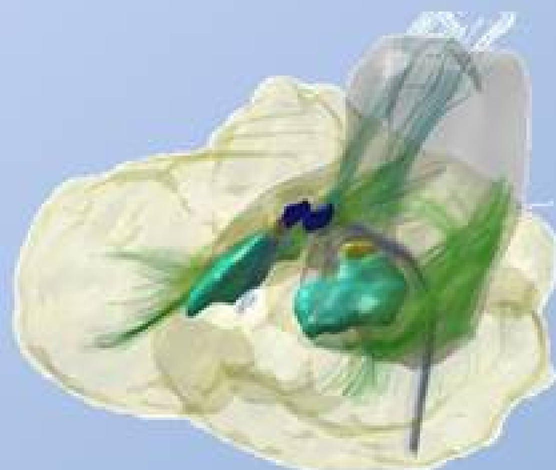
Overview

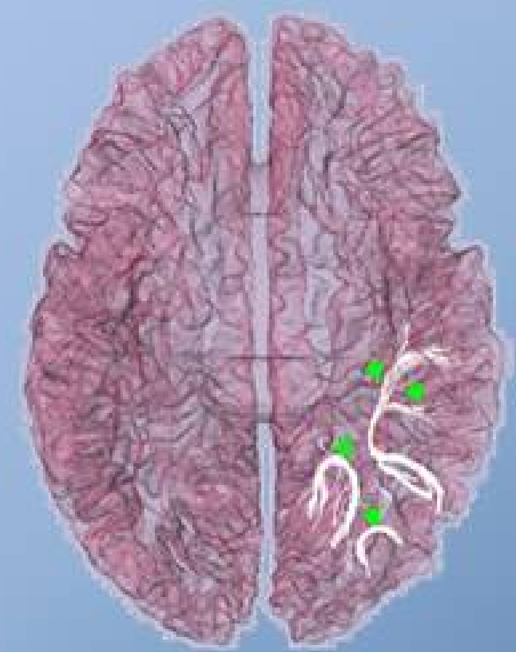
- Background
- Signal and Noise in DW-MRI
- Diffusion Tensor Imaging
- Q-Space Imaging
- Conclusion
- **Future Directions**



Clinical Applications

- Development of Biomarkers
  - MS lesion and normal appearing white matter
  - Spinocerebellar ataxia
- Targeted Acquisitions and Modeling
  - Spinal cord
    - MS/traumatic injury
  - Cerebellum/brainstem
    - Neurodegeneration
- Informatics

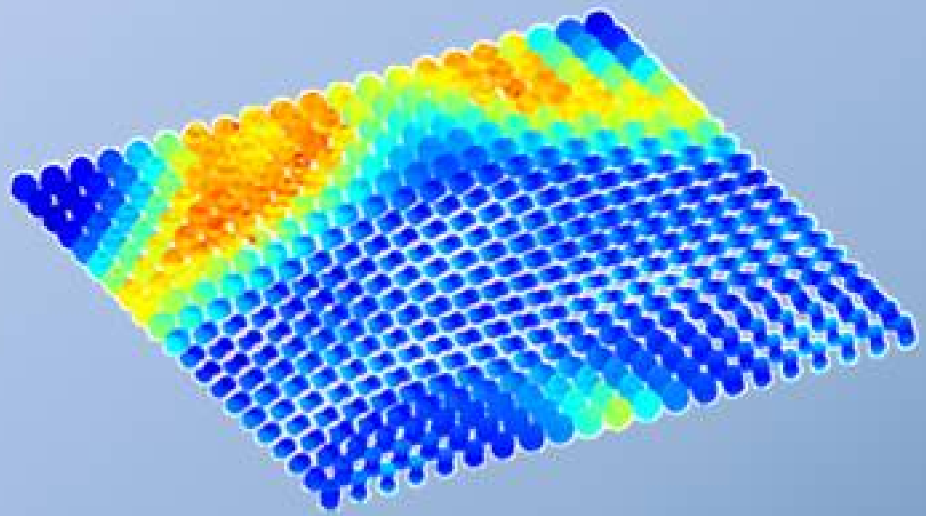




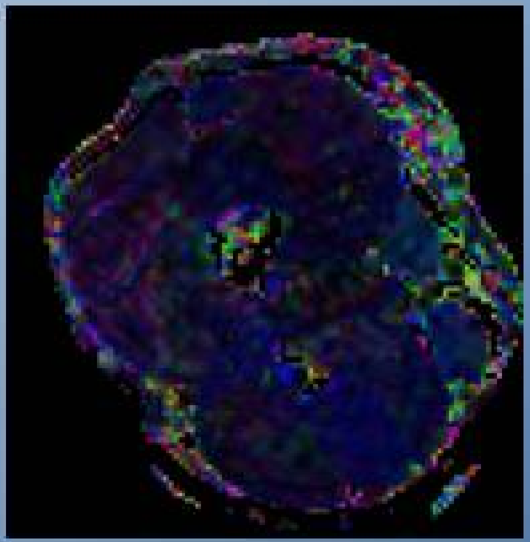
Emerging DW-MRI

- Non-tensor DW-MRI
  - High angular resolution
  - High q-value
  - Multiple b-values and directions
- Non-traditional DW imaging targets
  - Peripheral nerves
  - Musculoskeletal
  - Cardiac muscle

High Angular Resolution Diffusion Imaging

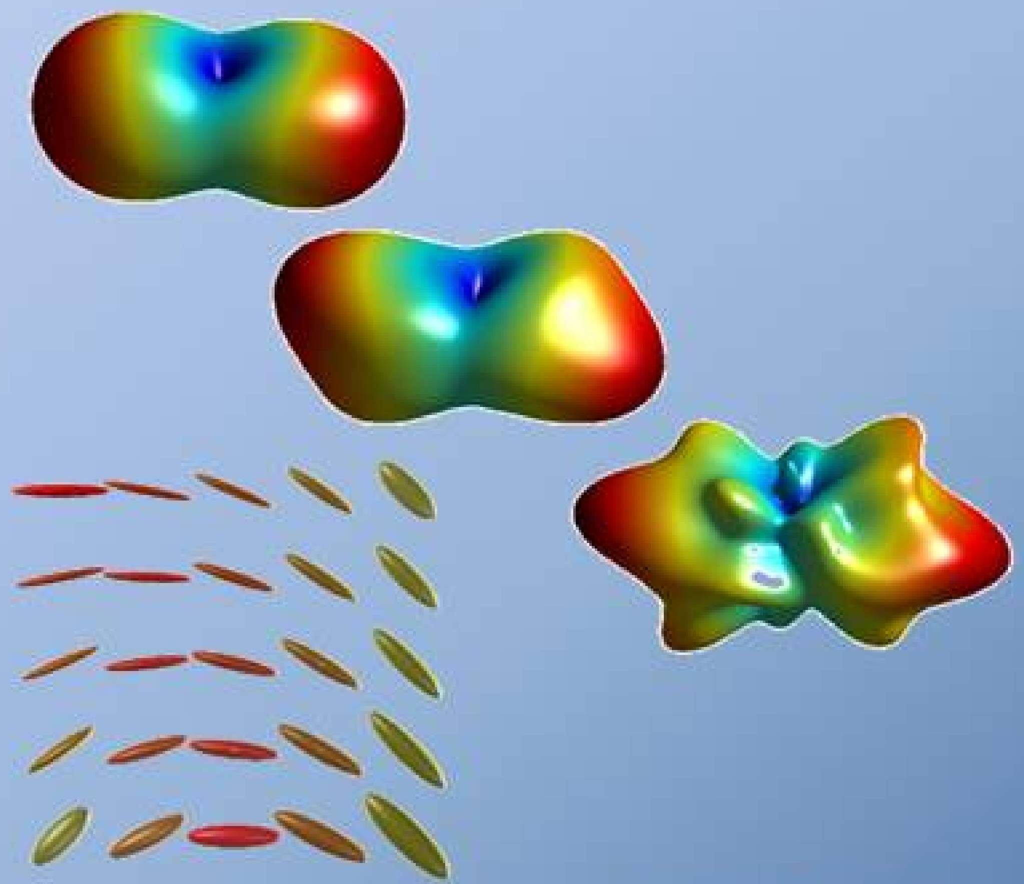


Musculoskeletal DW MRI

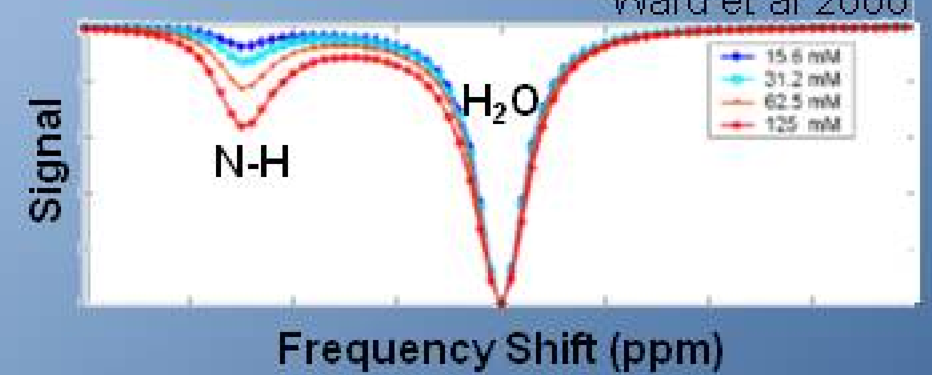


Statistical Analysis

- Hypothesis testing and model selection
  - Multi-dimensional/multi-modal characterization
  - Atlasing building
    - Interpolation
    - Metrics
- Quantitative Imaging
  - Metabolic imaging with Chemical Exchange Saturation Transfer (CEST)



Ward et al 2000



Thank you.

Thesis Committee

- Carey Priebe
- Jerry Prince
- Larry Schramm
- Susumu Mori
- Sarah Ying

Research Groups

- Image Analysis and Communications Lab
- F.M. Kirby Research Center
- Ataxia Research Center
- Center for Magnetic Resonance Microimaging

In particular…

- Alex Sinofsky
- Amy Ruppel
- Andrew Liu
- Baohan Pan
- Ewa Kulikowicz
- Hao Huang
- Harsh Agarwal
- Howard Ying
- Jay Burns
- Jiangyang Zhang
- John Bogovic
- Jonathan Farrell
- Jon Freedlander
- Mark Teaford
- Meenal Patel
- Nera-Lee Patel
- Pelin Aksit
- Peter van Zijl
- Phillip Randy Brown
- Seth Smith
- Sue Eller
- Shwetadwip Chowdhury
- Stewart Mostofsky
- Wade Mayes

Slides available at: http://iacl.ece.jhu.edu/~bennett

References I

- **Basser & Jones 2002** : Basser, P.J. and D.K. Jones, *Diffusion-tensor MRI: theory, experimental design and data analysis - a technical review*. NMR Biomed, 2002. 15(7-8): p. 456-67.
- **Cohen & Assaf 2002** : Cohen, Y. and Y. Assaf, *High b-value q-space analyzed diffusion-weighted MRS and MRI in neuronal tissues - a technical review*. NMR Biomed, 2002. 15(7-8): p. 516-42.
- **Cory & Garroway** : Cory, D.G. and A.N. Garroway, *Measurement of translational displacement probabilities by NMR: an indicator of compartmentation*. Magn Reson Med, 1990. 14(3): p. 435-44.
- **Kaufman et al 1989** : Kaufman L, Kramer DM, Crooks LE, Ortendahl DA. Measuring signal-to-noise ratios in MR imaging. Radiology 1989;173:265-267.
- **Landman et al 2007a** : B. A. Landman, P-L. Bazin, and J. L. Prince. "Diffusion Tensor Estimation by Maximizing Rician Likelihood", In *Proceedings of the 2007 International Conference on Computer Vision Workshop on Mathematical Methods in Biomedical Image Analysis*, Rio de Janeiro, Brazil, October 2007.
- **Landman et al 2008a** : B. A. Landman, P-L. Bazin, and J. L. Prince, "Robust Diffusion Tensor Estimation by Maximizing Rician Likelihood," *International Society for Magnetic Resonance in Medicine*, Toronto, Canada, May 2008
- **Landman et al 2008b** : B. A. Landman, P-L Bazin, J. L. Prince, "Robust Estimation of Spatially Variable Noise Fields: Applications to Diffusion Tensor Imaging", *NeuroImage*, Submitted February 2008
- **Landman et al 2008c** : B. A. Landman, P-L. Bazin, and J. L. Prince, "Robust Diffusion Tensor Estimation by Maximizing Rician Likelihood," *International Society for Magnetic Resonance in Medicine*, Toronto, Canada, May 2008
- **Landman et al 2008d** : B. A. Landman, J. A.D. Farrell, S. A. Smith, P. C.M. van Zijl, and J. L Prince, "Q-Space Diffusion Weighted MRI Analyzed with Maximizing Rician Likelihood Improves Reliability and Tissue Contrast," *International Society for Magnetic Resonance in Medicine*, Toronto, Canada, May 2008

References II

- **Landman et al 2008e** : B. A. Landman, J. A.D. Farrell, S. A. Smith, P. A. Calabresi, P. C.M. van Zijl, and J. L Prince, "Exploring the Information Content of q-Space Diffusion Weighted Imaging: Application to Multiple Sclerosis (MS) Spinal Cord Lesions," *International Society for Magnetic Resonance in Medicine*, Toronto, Canada, May 2008
- **Norris 2001** : Norris, D.G., *The effects of microscopic tissue parameters on the diffusion weighted magnetic resonance imaging experiment*. NMR Biomed, 2001. 14(2): p. 77-93.
- **Pyramis 2004** : SilviusPro 3D Dissector and Atlas of the Human CNS, Pyramis Studios Inc. 2004
- **Smith et al 2008** : S. A. Smith, V. Belegu, B. A. Landman, B. A. Chodkowski, J. A. Farrell, P. C. van Zijl, and J. W. McDonald. "Quantitative Assessment of Traumatic Spinal Cord Injury with Diffusion Tensor and Magnetization Transfer MRI," *International Society for Magnetic Resonance in Medicine*, Toronto, Canada, May 2008
- **Stejskal & Tanner 1965** : Stejskal, E.O. and J.E. Tanner, *Spin diffusion measurements: spin echoes in the presence of a time-dependent field gradient*. *J Phys Chem*, 1965. 42: p. 288-292.
- **Ward et al 2000** : Ward KM, Aletras AH, Balaban RS. A new class of contrast agents for MRI based on proton chemical exchange dependent saturation transfer (CEST). J Magn Reson 143(1): 79-87, 2000