POLYTECHNIQUE MONTRÉAL

Université de Montréal

Diffusion Basis Spectrum Imaging

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BMDE 660 Final Project

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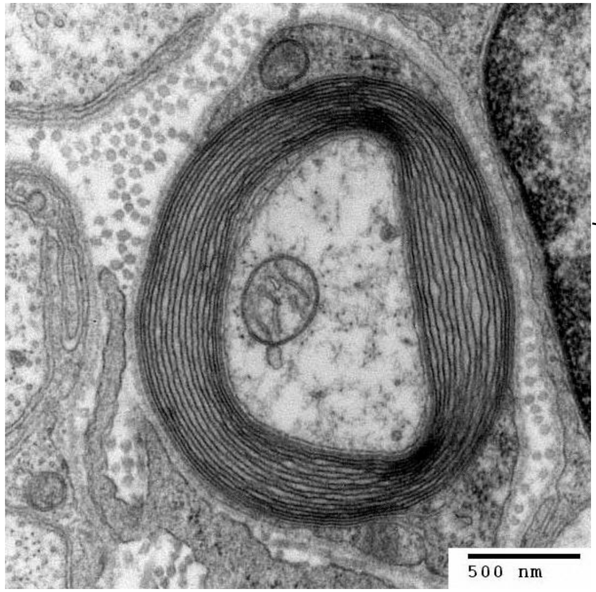
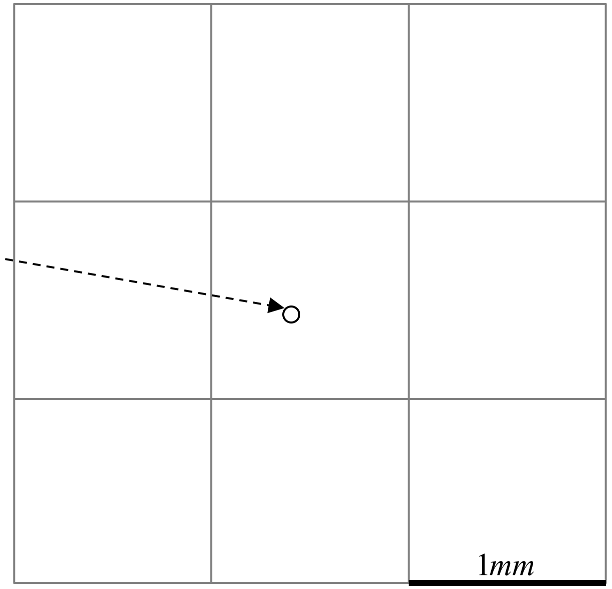
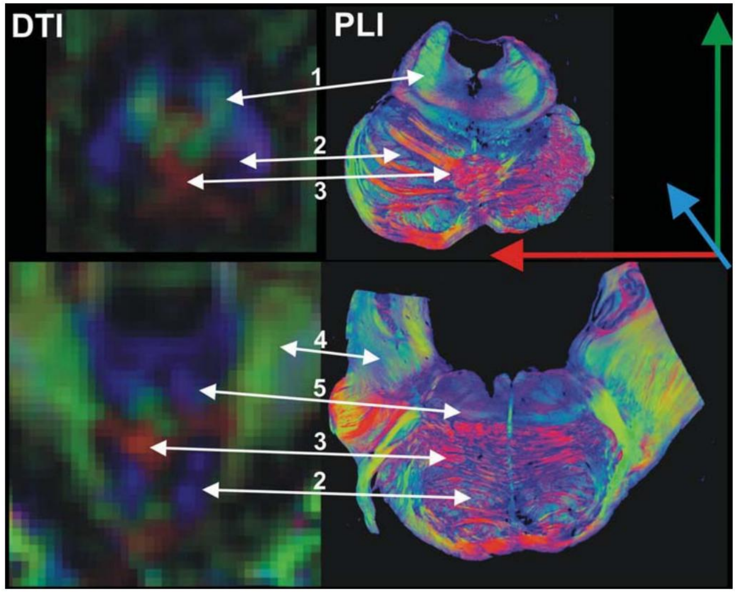
Different Resolutions of Imaging Method



TEM: $0.2nm$



MRI: $1-2mm$



DTI: $2mm$ PLI: $200\ nm$

- Typical diameter of neural fiber $0.1-20um$
- Cytoskeleton of the axon: $8-25nm$

Time-consuming: $3um \times 3um$ $40\min$

Sample making complicated

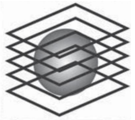
No vivo imaging

Low resolution (limited by principle)

Groups of fibers in one voxel

100ms to seconds

Vivo imaging



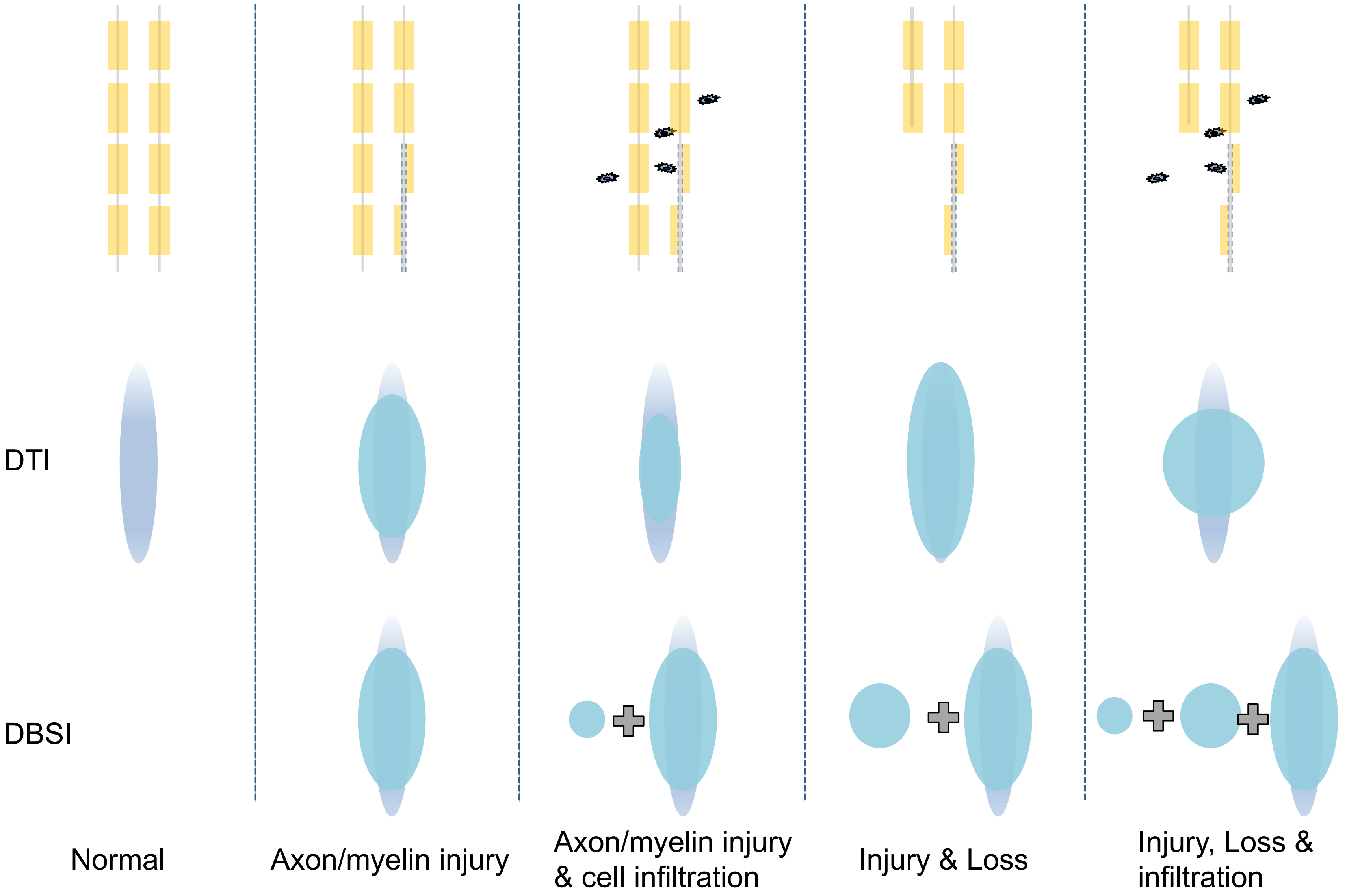
Microseconds

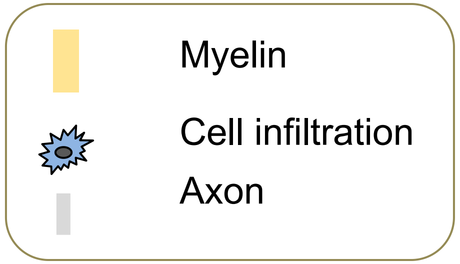
Elaborate processing of tissue

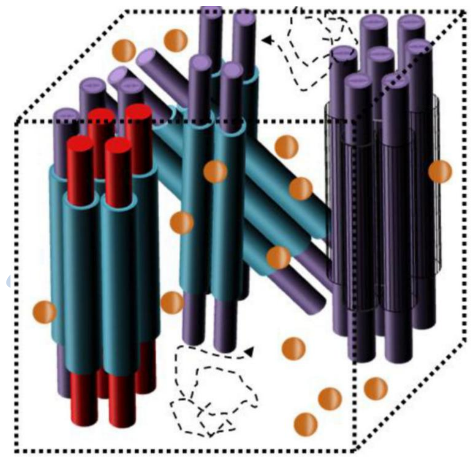
no vivo imaging

The only way to investigate WM of the living brain, but low resolution

Purpose

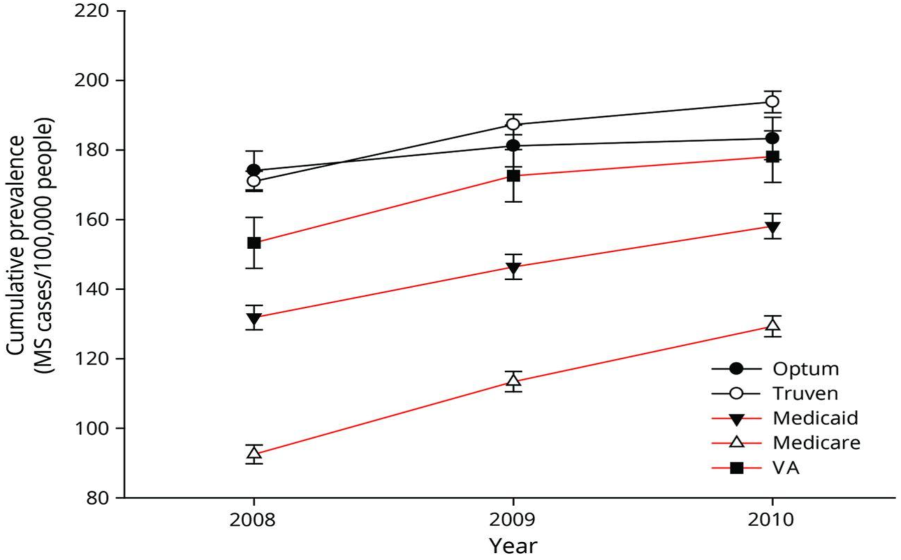


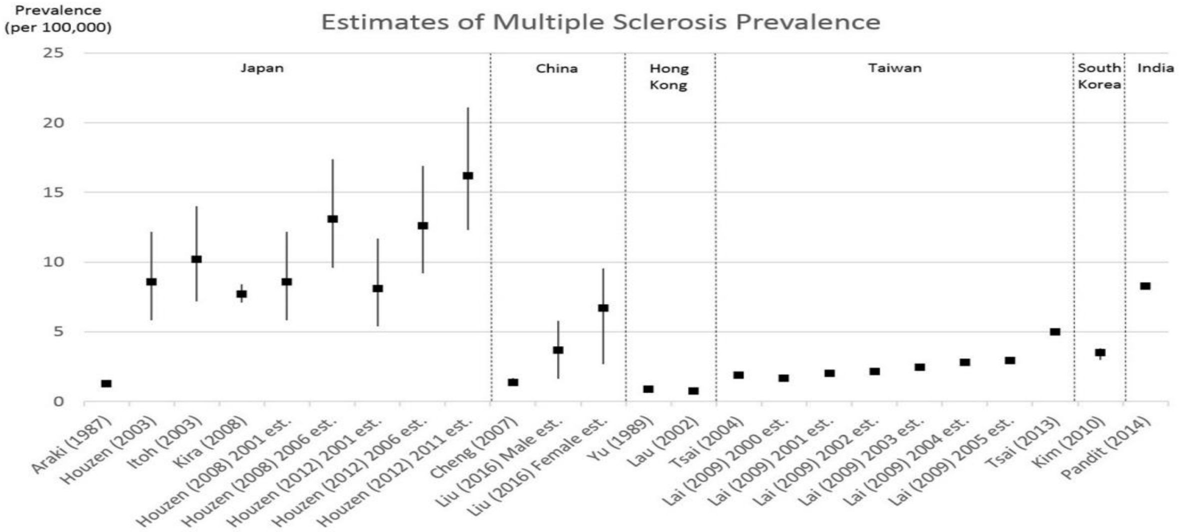


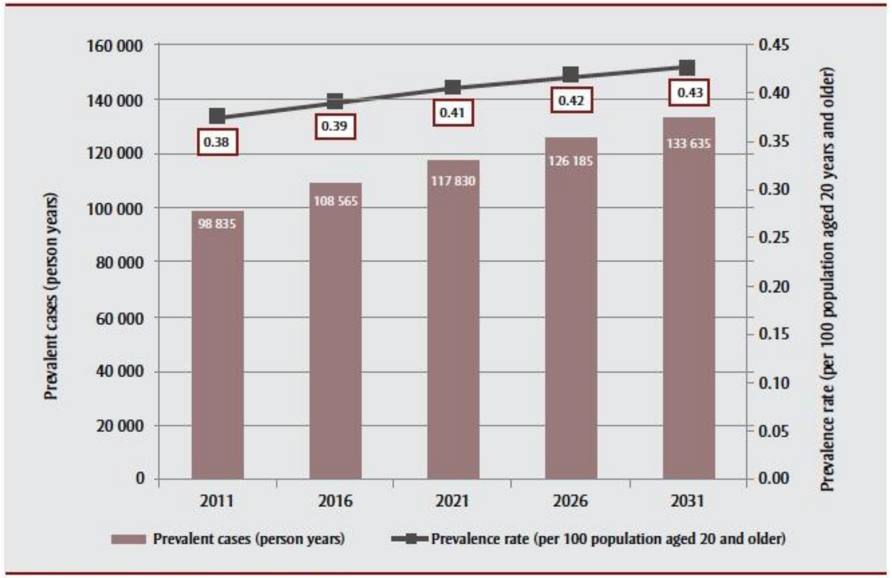


Purpose:
- Accurate neural architecture information (crossing fibers);
- Estimate diffusion parameters (extra-fiber pathology)

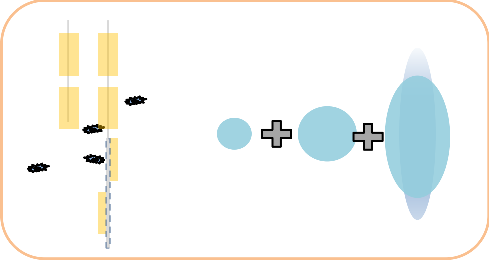
Clinical applications







Abbreviation: POHEM, Population Health Model.



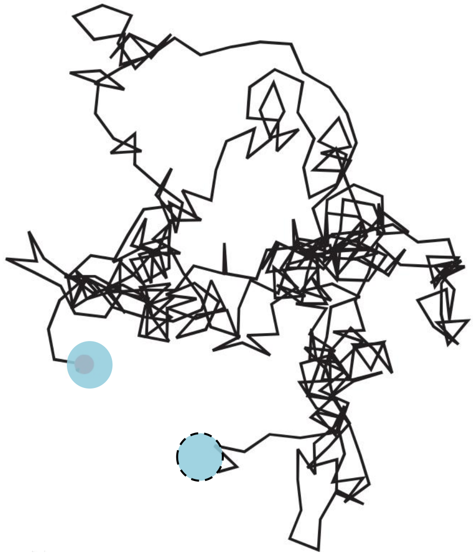
Neurological diseases:

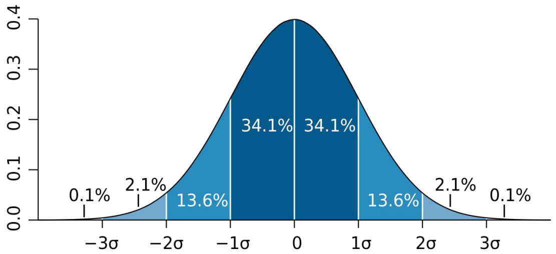
- Mutiple sclerosis
- Epilepsy
- Cervical spondylotic myelopathy
- Intracranial inflammation in HIV+ patients

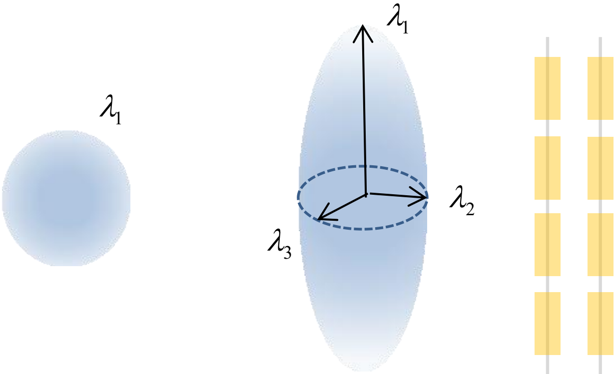
Applications:

- Accurately assess MS progression and the disease modifying interventions;
- Earlier diagnoise, long-term prediction
- Research on Children CNS development
- Solving fiber tracking problem

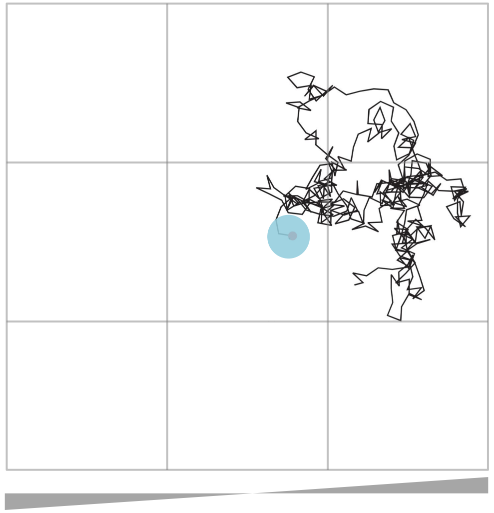
Basic DTI







$$\begin{bmatrix}\lambda_1\\ \lambda_2\\ \lambda_3\end{bmatrix}\times\begin{bmatrix}\lambda_1 & \lambda_2 & \lambda_3\end{bmatrix}=\begin{bmatrix}D_{xx} & D_{xy} & D_{xz}\\ D_{yx} & D_{yy} & D_{yz}\\ D_{zx} & D_{zy} & D_{zz}\end{bmatrix}$$



$$\frac{S(TE)}{S(0)}=e^{-bD} \qquad b=(rG\delta)^2(\Delta-\frac{\delta}{3})$$

Diffusion constant

- Diffusion constant
- Watermolecular mobility
- Gaussian distribution
- 1D: $\bar{x^2}=2D\cdot t$
- 3D: $\bar{x^2}=6D\cdot t$

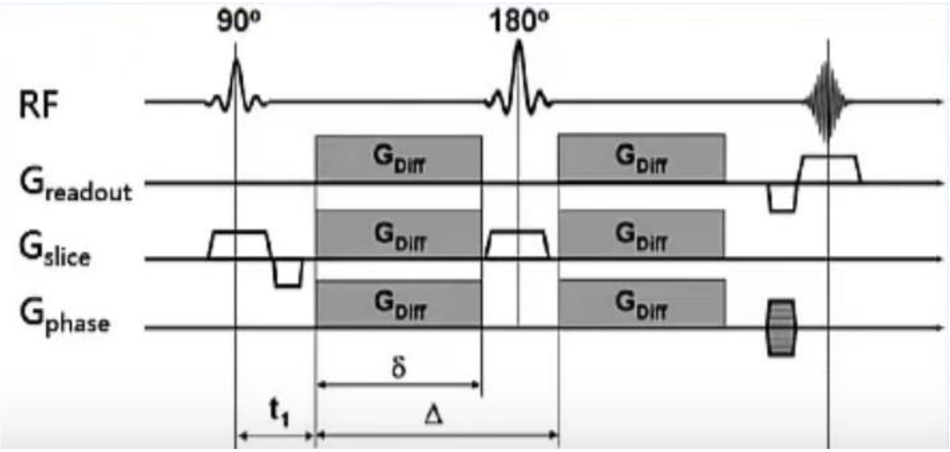
Diffusion Tensor

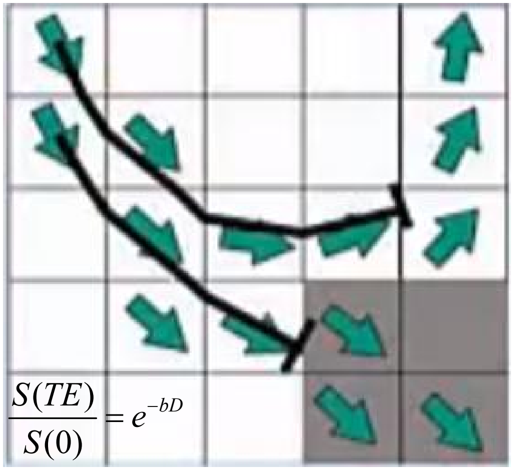
- 3 by 3
- Free water: ball, isotropic
- Restricted water (fiber): ellilpsoid, uanisotropic
- if symmetrical: 6 unknowns

Gradient and signal

- b
- b and D make signal reduction
- b0 and at least 6 imaging with different b
- Find diffuison tensor

Fiber Tracking



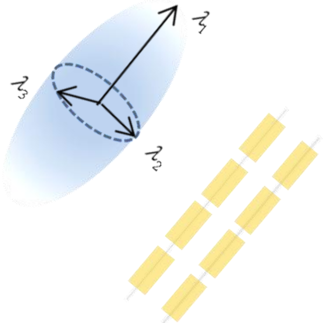


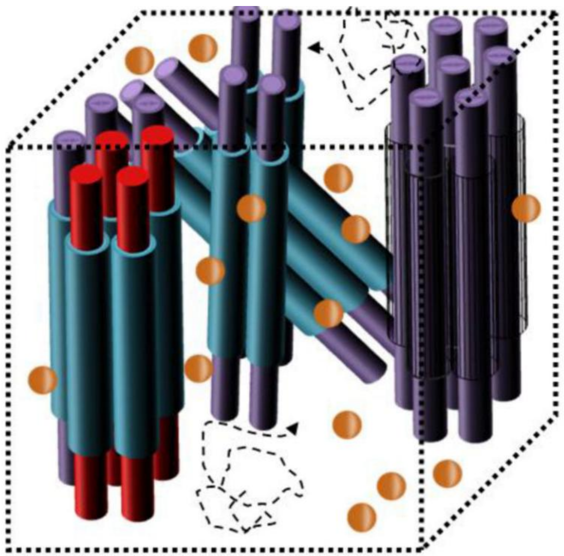
Fiber tracking
- ➢ Turning angle smaller than 60 degree
- ➢ FA too small
- ➢ Fails to track more than 1 fiber in 1 voxel

$$\begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} \times \begin{bmatrix} b_x & b_y & b_z \end{bmatrix} = \begin{bmatrix} b_{xx} & b_{xy} & b_{xz} \\ b_{yx} & b_{yy} & b_{yz} \\ b_{zx} & b_{zy} & b_{zz} \end{bmatrix}$$

$$\begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_6 \end{bmatrix} = \begin{bmatrix} b_{1xx} & b_{1yy} & b_{1zz} & b_{1xy} & b_{1xz} & b_{1yz} \\ b_{2xx} & b_{2yy} & b_{2zz} & b_{2xy} & b_{2xz} & b_{2yz} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ b_{6xx} & b_{6yy} & b_{6zz} & b_{6xy} & b_{6xz} & b_{6yz} \end{bmatrix} \times \begin{bmatrix} D_{xx} \\ D_{yy} \\ \vdots \\ D_{yz} \end{bmatrix}$$

$$\begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{bmatrix}$$





$$S_k = \sum_{i=1}^{N_{aniso}} C_i e^{-b_k \cdot D_i} + \eta$$

Gaussian Mixture Model:
- ➢ Assumption: independent fiber groups
- ➢ Try to solve: C_i, D_i, N

Advantage:
- ➢ Good angular resolution
- ➢ Fit well with muti-fiber voxels

Problem
- ➢ One group fiber problem
- ➢ Large dataset needed (accquizatio time)
- ➢ Nonlinear optimization problems (time)

Diffusion Basis Model

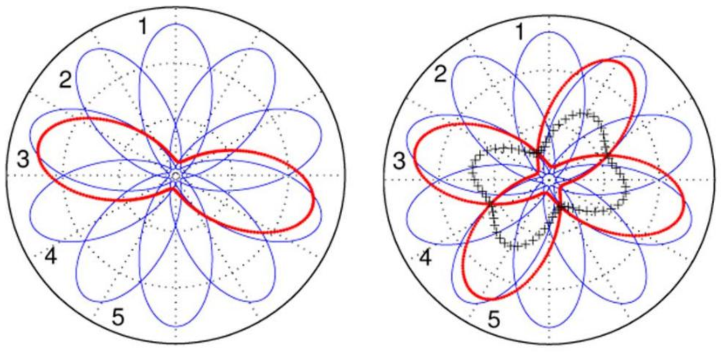
$$S_k = \sum_{i=1}^{N_{aniso}} C_i e^{-b_k \cdot D_i} + \eta \qquad \sum C_i = 1$$

Gaussian Mixture Model Problem Source:

- Large unknowns of diffusion tensors
- Nonlinear problem

Fixed set of tensors:

- Anisotropy and magnitude of water diffusion for each fiber is constant
- Choose DT accroding prior knowledge
- Try to solve linear problem



$$S_k = \sum_{i=1}^{N_{aniso}} C_i e^{-|\bar{b_k}|\lambda_\perp} e^{-|\bar{b_k}|(\lambda_{||}-\lambda_\perp)\cos^2\theta_{ik}} + \eta \qquad \sum C_i = 1$$

Diffusion Basis Model:

Advantage:

- Good angular resolution
- Fit well with one and muti-fiber voxels
- Linear optimization problem
- Degree of freedom reduced by using diffussion basis (small dataset)

Problems:

- No isotropic part, which may worse angular resolution

$$S_k = \sum_{i=1}^{N_{aniso}} C_i e^{-|\bar{b_k}|\lambda_\perp} e^{-|\bar{b_k}|(\lambda_{||}-\lambda_\perp)\cos^2\theta_{ik}} + C_{N+1} e^{-|\bar{b_k}| d_{iso}}$$

Solved:

- Ci and θ_{ik}
- Number of anisotropic tensors

DBSI Model

$$S_k = \sum_{i=1}^{N_{aniso}} C_i e^{-|\bar{b_k}|\lambda_\perp} e^{-|\bar{b_k}|(\lambda_{||}-\lambda_\perp)\cos^2\theta_{ik}} + C_{N+1} e^{-|\bar{b_k}| d_{iso}}$$

Diffusion Basis Model Problems:

- Can not known if injury axons and myelins or edema exist

Reasons:

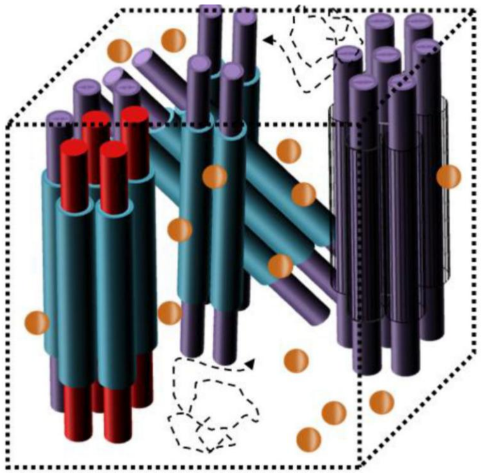
- Fixed diffusion tensors

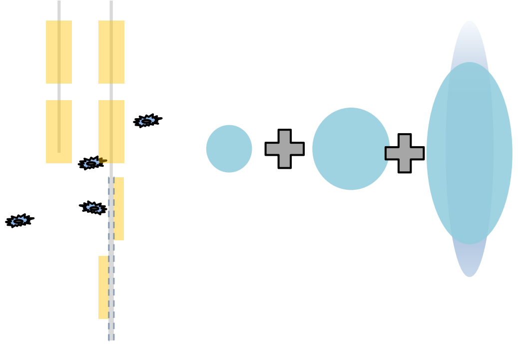
Nonlinear optimization problem:

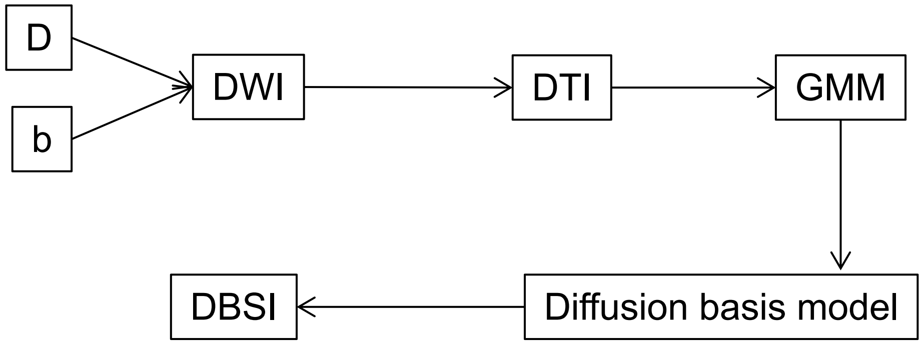
- know number of anisotropic tensors and its directions
- Try to solve $f_i,\quad f(D)$

How?

- Randomly select $\lambda_{||i},\quad \lambda_{\perp i}$
- Find best $f_i,\quad f(D)$ (least squart root method) and generalized pattern search algorithm to avoid local minimum
- Calculate the difference
- Repeat and find the smallest difference parameters
- Got $\lambda_{||i},\quad \lambda_{\perp i},\quad f_i,\quad f(D)$

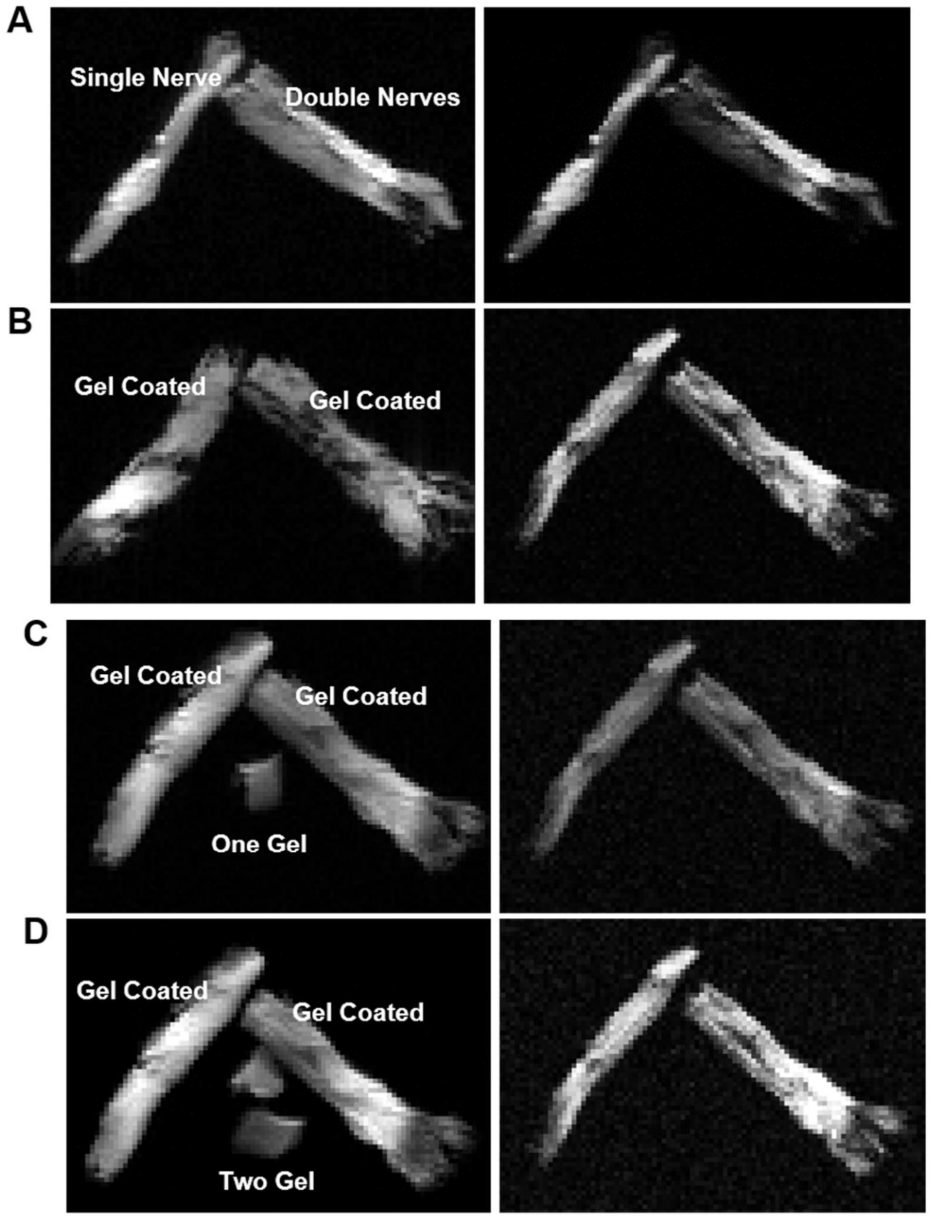


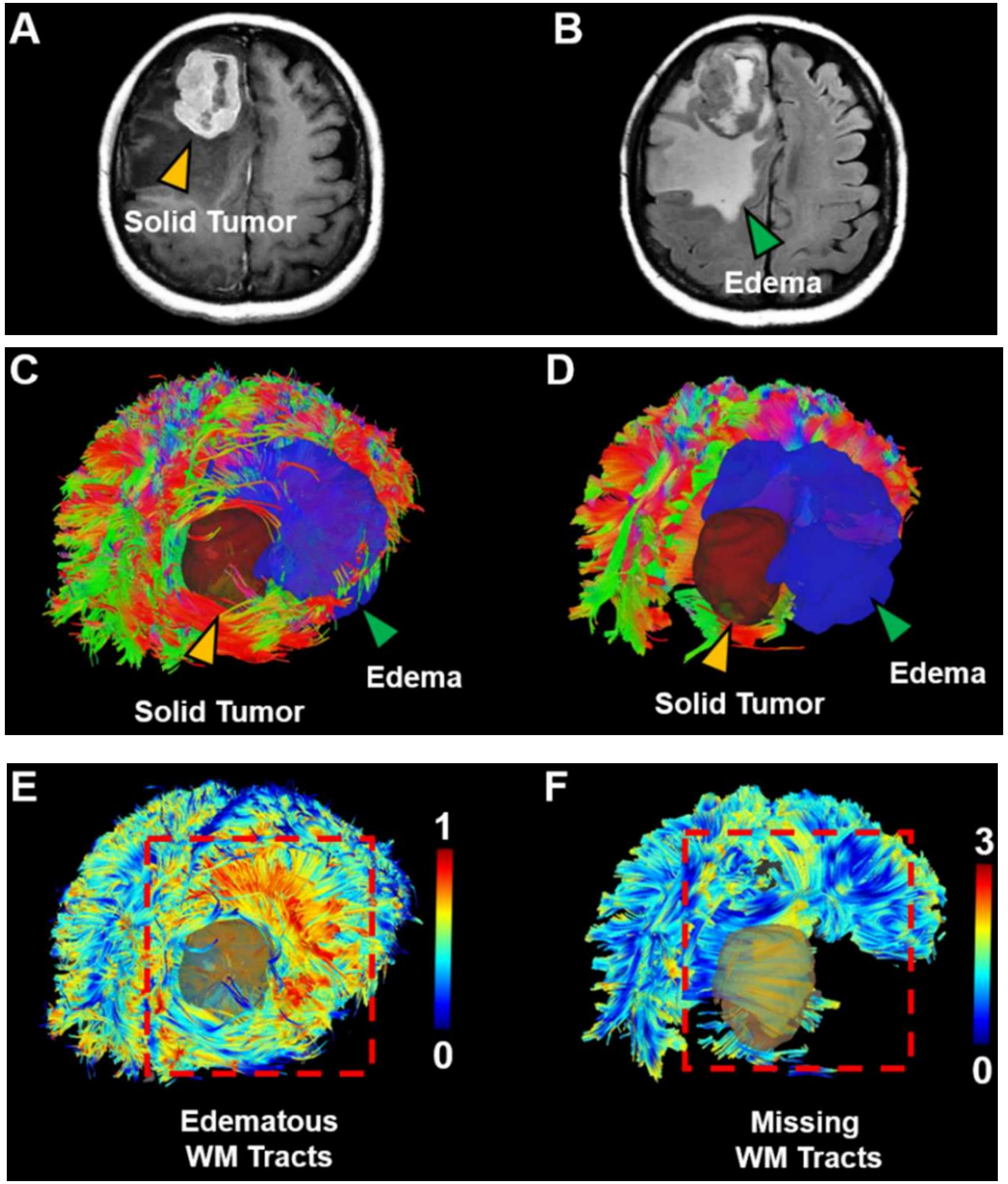




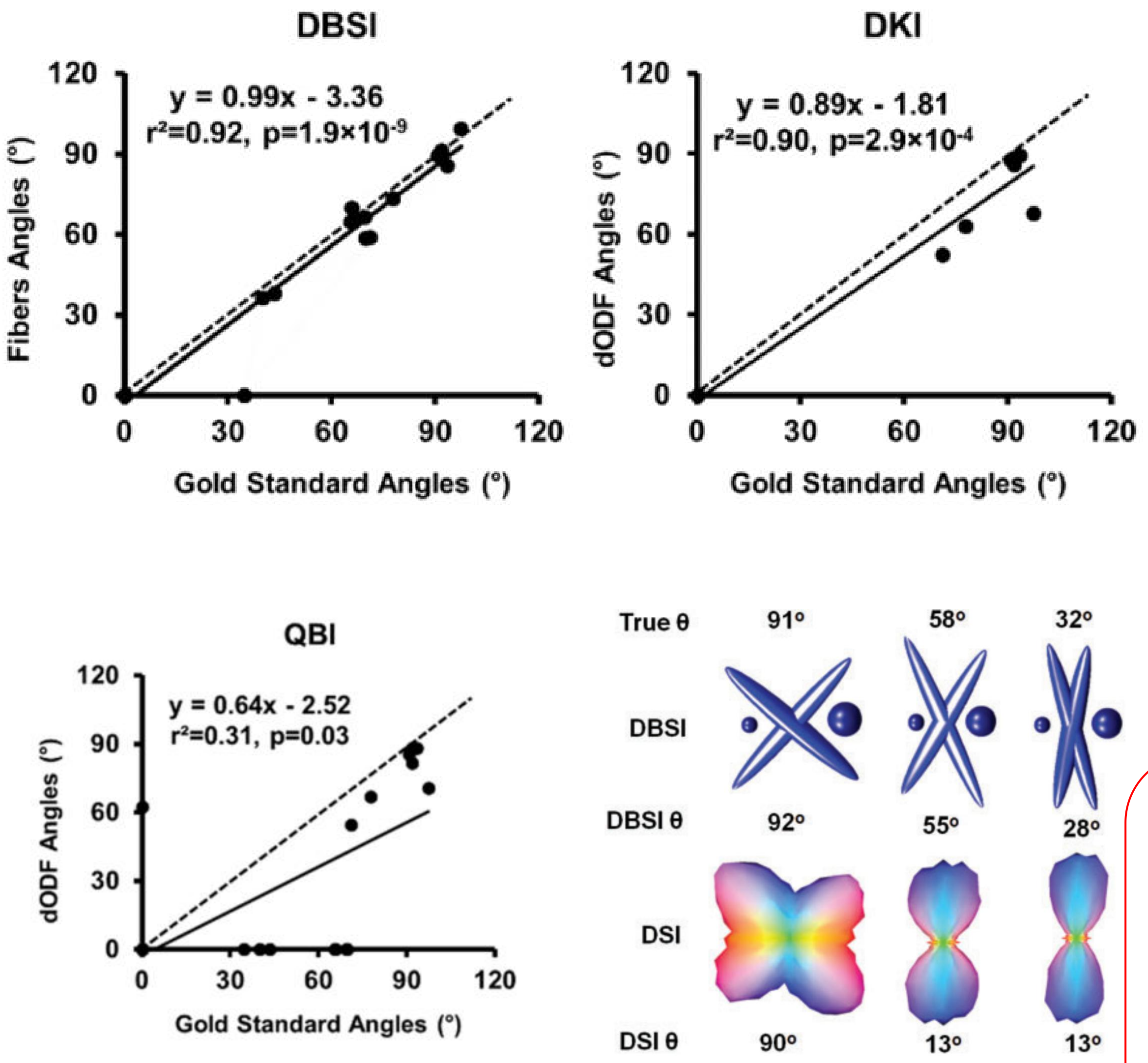
$$S_k = \sum_{i=1}^{N_{Aniso}} f_i e^{-|\bar{b_k}|\cdot\lambda_{\perp i}} e^{-|\bar{b_k}|\cdot(\lambda_{||i}-\lambda_{\perp i})\cdot\cos^2\psi_{ik}} + \int_a^b f(D) e^{-|\bar{b_k}|\cdot D}$$

Results


A
Single Nerve
Double Nerves
B
Gel Coated
Gel Coated
C
Gel Coated
Gel Coated
One Gel
D
Gel Coated
Gel Coated
Two Gel


A
Solid Tumor
B
Edema
C
Solid Tumor
Edema
D
Solid Tumor
Edema
E
1
0
Edematous
WM Tracts
F
3
0
Missing
WM Tracts

Results, challenges & Conclusion



Challenges:

If number of anisotropic tensors is large, not efficiency or the nolinear optimization problem, time cost.

- ➢ First fix axonal diffusivity, find best radial diffusivities.
- ➢ The use radial diffusivities to find best axonal diffusivities.
- ❖ Fibers in voxels adjacent are not independent, use former voxel information to as the start values of later one.

Diffuisivity of fibers may not be independent.

- ➢ Use different b values with same directions to detect if fibers are indepentdent or not.

Fiber positions in one voxel

- ➢ Independet fiber take more sparse space

Conclusion:

- ❖ DBSI method assume that fibers are independent in each voxel, and its diffuisivities can be added;
- ❖ It use fixed diffusion functons as basis;
- ❖ Can seperate isotropic parts from different anistropic parts in tissues;
- ❖ Has high angular resolution and fiber tracking abilities;
- ❖ Have great potentials in applications of CNS diseases

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