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Diffusion in Python

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DIPY

- Free and open source software project for computational anatomy in Python.

- It focuses on diffusion MRI analysis but also contains algorithms that are generic for medical imaging e.g. denoising, registration.

- DIPY is an international project which brings together scientists **across labs and countries …**

- … to share their **state-of-the-art code** and expertise in the same codebase, accelerating scientific research in medical imaging.

DIPY

- More than 100 contributors from more than 30 Universities & Institutions

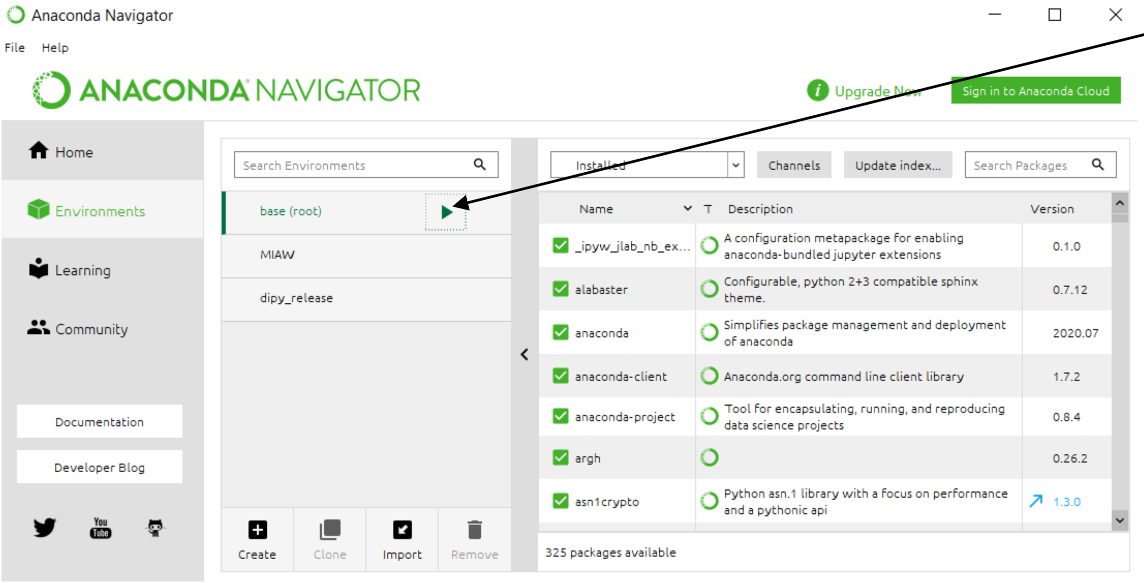
https://github.com/dipy/dipy/graphs/contributors

Dipy Installation

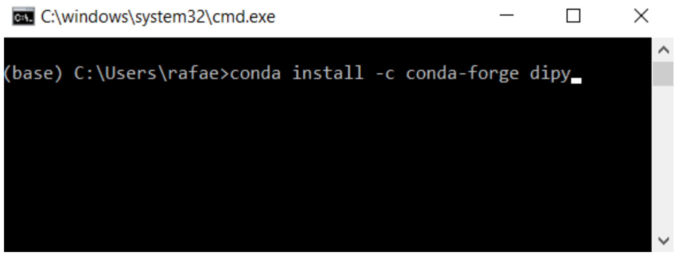
DIPY

- To install all python dependencies, we recommend to install first anaconda (https://www.anaconda.com/).

- After Anaconda installation, open the Anaconda Navigator App



To open a terminal press this button



Type in the terminal:

conda install -c conda-forge dipy

Dipy Installation

- Some of the visualization methods require the FURY library and this can be installed separately (for the time being only on Python 3.4+):

  pip install fury

- You can also install dipy using pip, for this you need to install first some of dipy dependencies:

  pip install nibabel

  pip install dipy

  pip install fury

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Why Diffusion MRI?

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Motivation – why diffusion MRI?

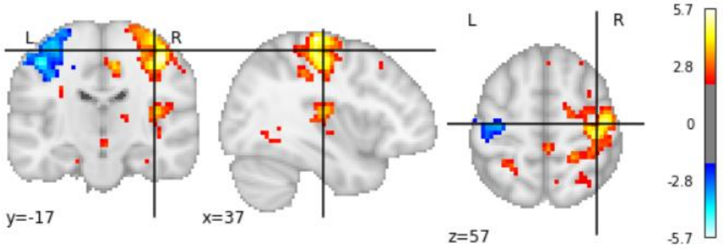
MRI allows the imaging the structure and function of entire tissues non-invasively

- Typical resolution: 1-2 mm

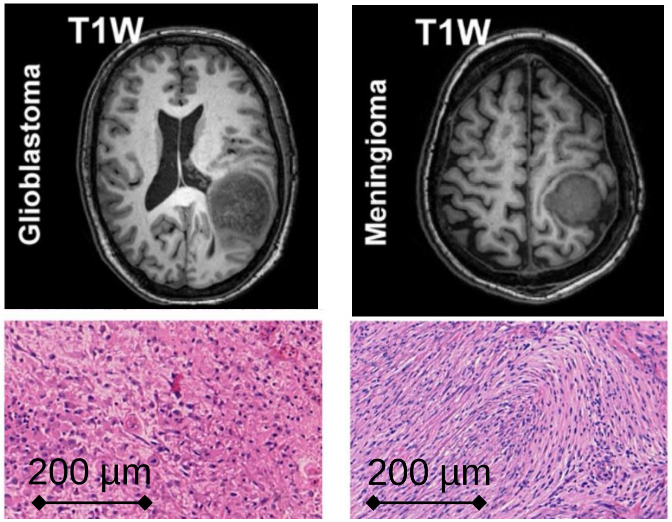
Diffusion MRI

But we may be interested in information related to lower resolutions

- Tissue maturation (myelination and axonal pruning)
- Tissue degeneration (axonal loss and demyelination)
- Characterization of pathologies



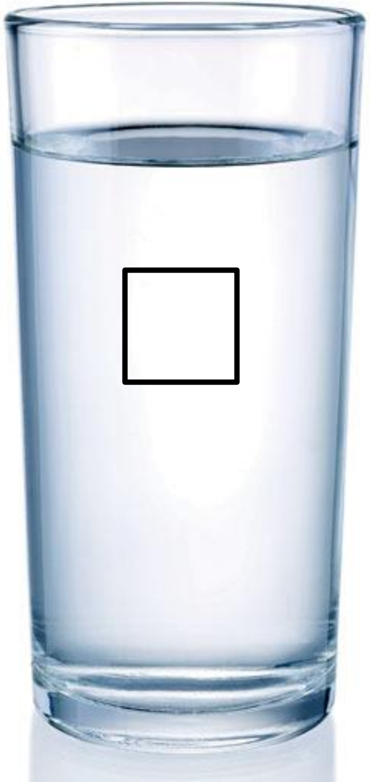
Michael's NILEARN tutorial (09/11/2020)



Adapted from Szczepankiewicz et al., Neuroimage 2015

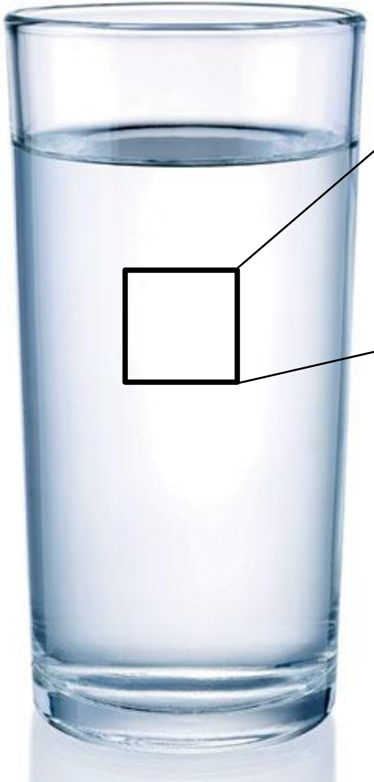
Motivation – what is diffusion?

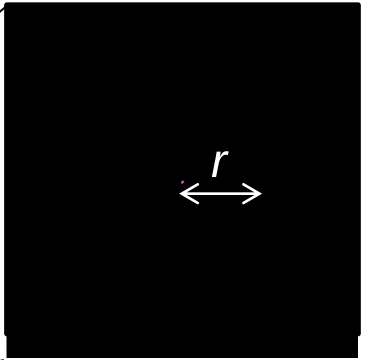
Free water diffusion



Motivation – what is diffusion?

Free water diffusion





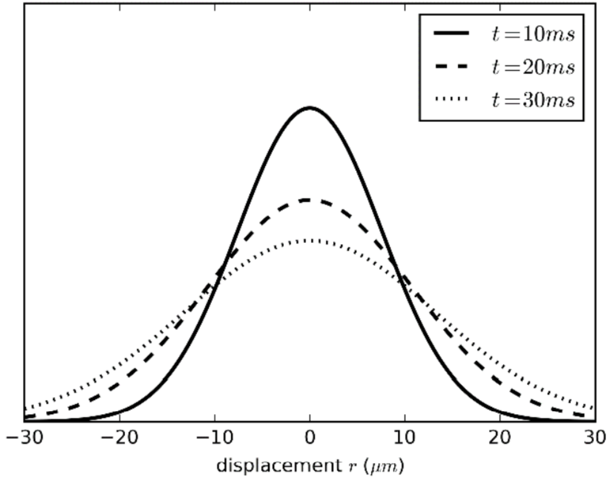
Brownian Motion

$D = 3\mu m^2/ms$

$t = 10\ ms$

$l_c \approx 7.7\mu\text{m}$

Displacement probability distribution



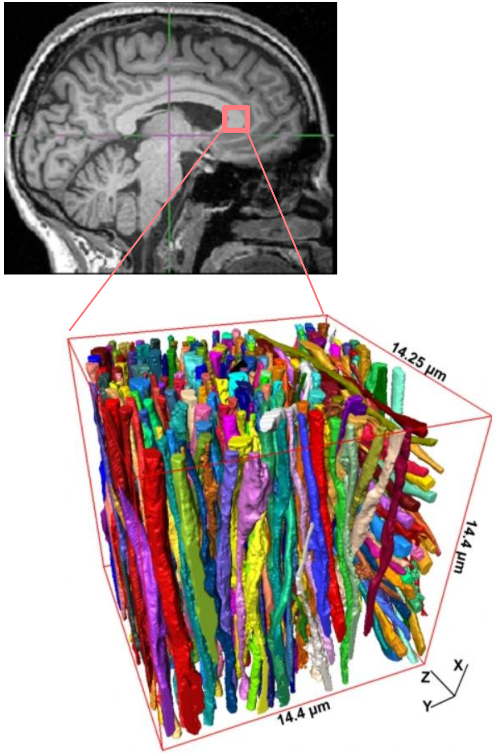
$\langle r^2 \rangle = 2Dt$

$l_c \equiv \sqrt{\langle r^2 \rangle}$

- Isotropic
- Gaussian

Motivation – what is diffusion?

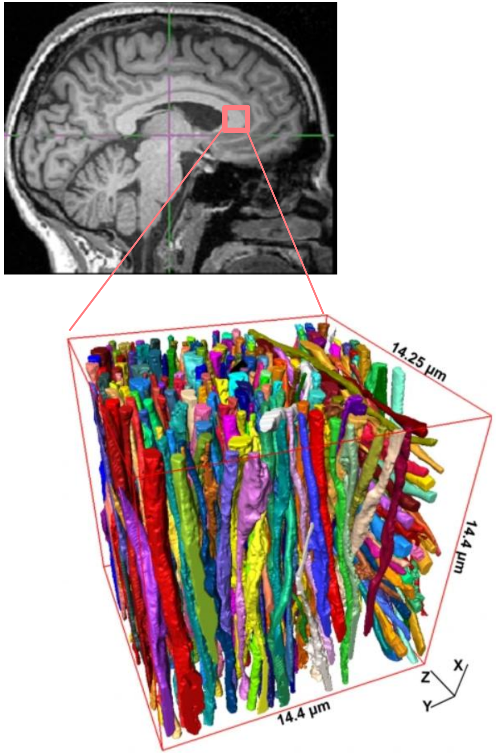
Diffusion in biological tissues



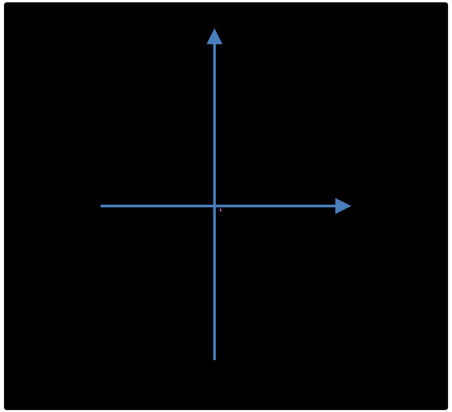
Adapted from Abdollahzadeh et al., Sci Rep 2019

Motivation – what is diffusion?

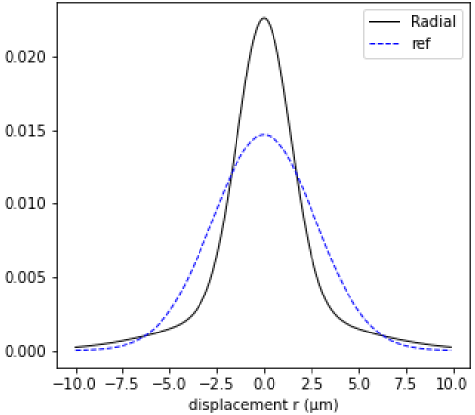
Diffusion in biological tissues

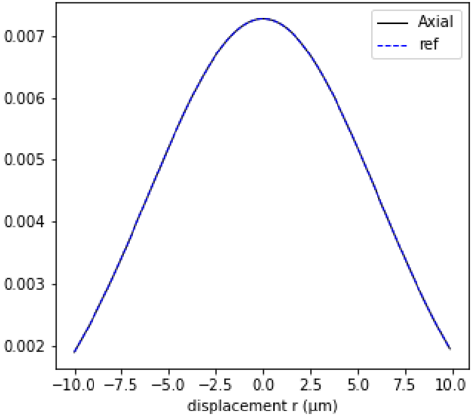


Adapted from Abdollahzadeh et al., Sci Rep 2019



- Anisotropic
- Non-Gaussian





Diffusion-weighted Magnetic Resonance Imaging (dMRI)

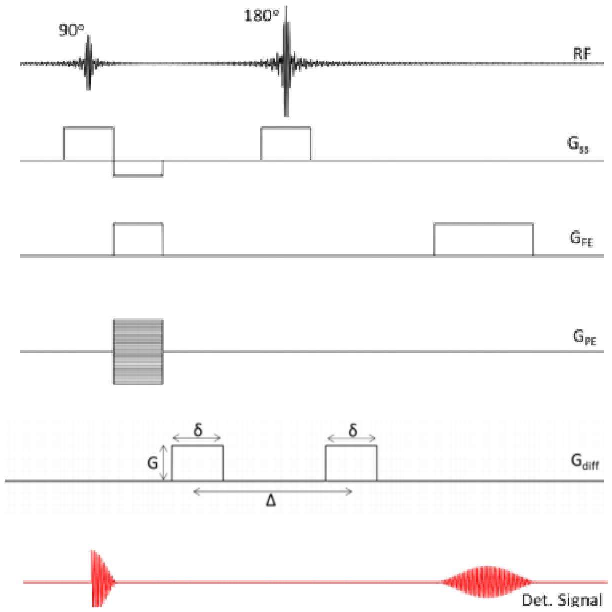
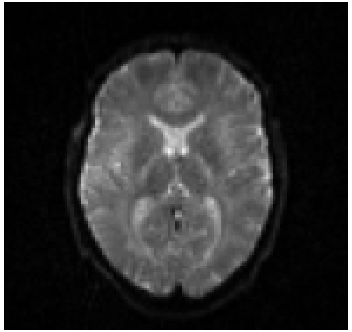


Illustration of a pulse diagram for a standard spin-echo sequence



Diffusion-weighted Magnetic Resonance Imaging (dMRI)

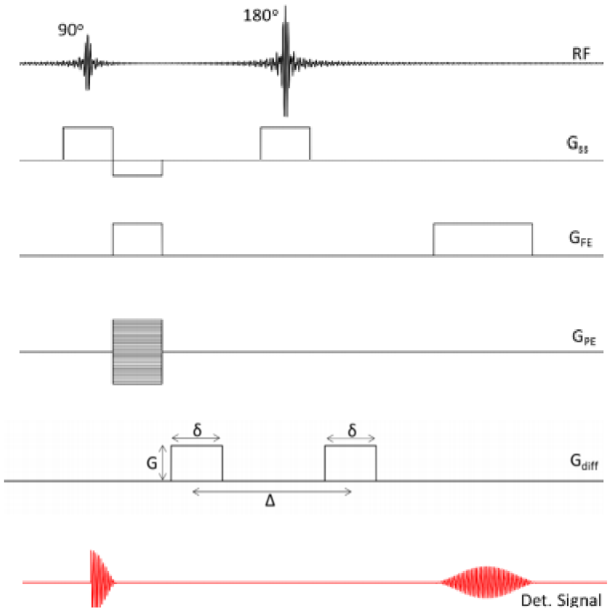
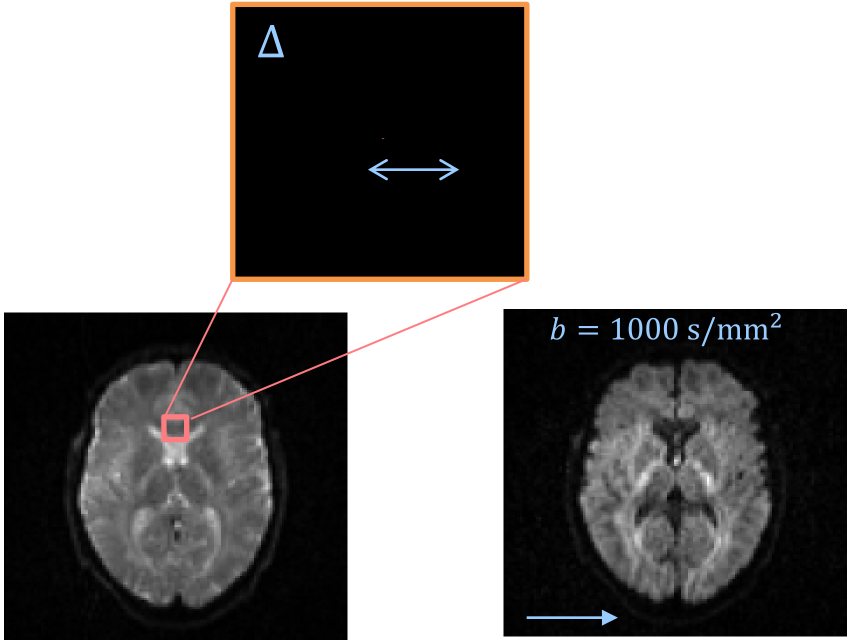


Illustration of a pulse diagram for a standard spin-echo sequence



$$S(b, \boldsymbol{n}) \approx S_0 \exp(-bD(\boldsymbol{n}))$$

$$b = \gamma^2 \delta^2 \left(\Delta - \frac{\delta}{3}\right) G^2$$

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Reconstructing DTI using Dipy

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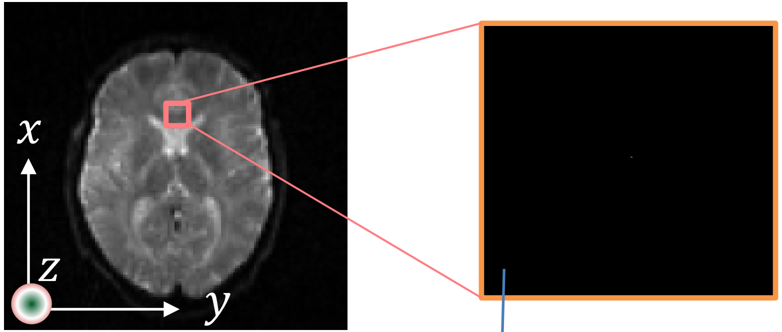
Diffusion Tensor Imaging (DTI)

- Diffusion Tensor Imaging (DTI) models diffusion in each voxel using a 2nd order tensor:

Basser et al. MRM 1994

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

Diffusion Tensor



For this voxel

$$\boldsymbol{D} = \begin{bmatrix} D_{xx} & 0 & 0 \\ 0 & D_{yy} & 0 \\ 0 & 0 & D_{zz} \end{bmatrix}$$

For the voxel sample

Axial diffusivity (AD) is the diffusion parallel to "fibres"

$$AD = D_{xx}$$

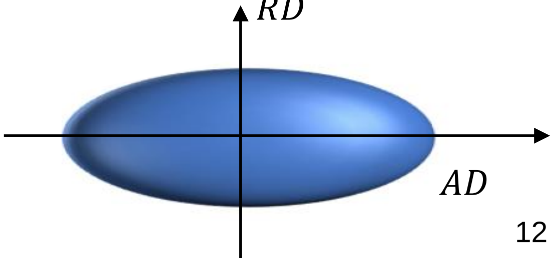
Radial diffusivity (RD) is the diffusion perpendicular to "fibres"

$$RD = (D_{yy}+D_{zz})/2$$

Mean diffusivity (MD) is the diffusivity averages across directions

$$\mathrm{M}D = (D_{xx} + D_{yy} + D_{zz})/3$$

– Ellipsoid representation



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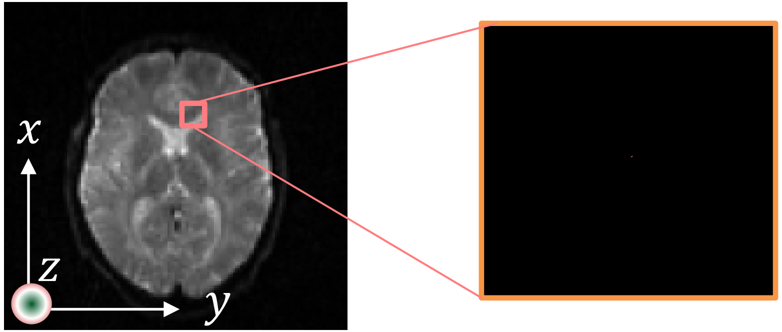
Diffusion Tensor

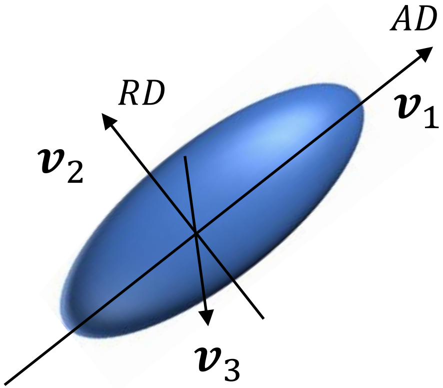


– AD, RD and MD can be more generally computed from eigen-value decomposition

$$\begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{bmatrix} = [\boldsymbol{v}_1 \quad \boldsymbol{v}_2 \quad \boldsymbol{v}_3] \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} \begin{bmatrix} \boldsymbol{v}_1 \\ \boldsymbol{v}_2 \\ \boldsymbol{v}_3 \end{bmatrix}$$

$$AD = \lambda_1 \qquad RD = (\lambda_2 + \lambda_3)/2 \qquad MD = (\lambda_1 + \lambda_2 + \lambda_3)/3$$

– Ellipsoid representation



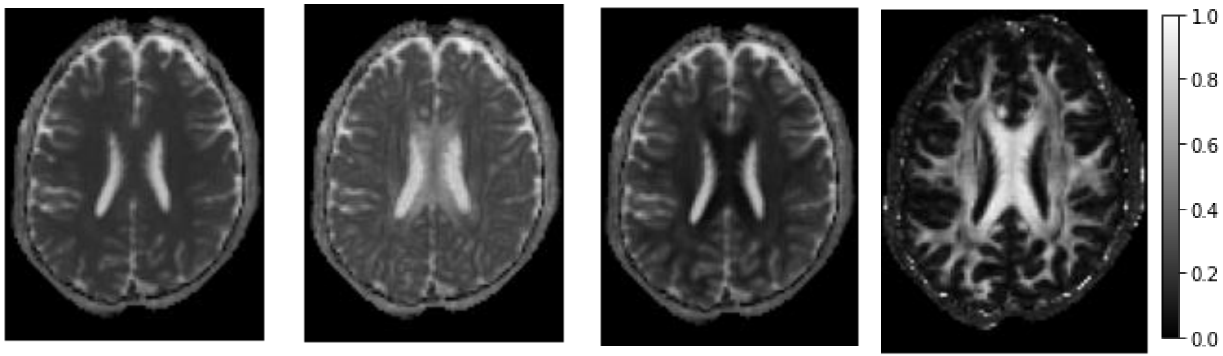
Diffusion Tensor Imaging

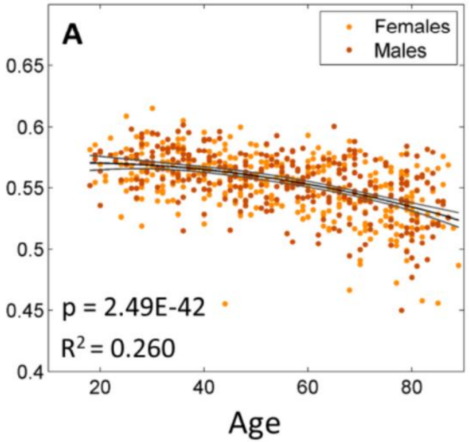
- Diffusion Tensor Imaging Model involves the fitting of the model:

$$S(b,\boldsymbol{n}) = S_0 \exp\left(-b\boldsymbol{n} \begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{bmatrix} \boldsymbol{n}^T \right)$$

  – In addition to S_0 acquisition, it requires at least the acquisition of six direction for a non-zero b-value

MD AD RD Fractional Anisotropy (FA)





  – FA is typically used as a marker of tissue maturation or degeneration

FA has a range from 0 to 1

 FA =0  FA =1

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Introduction to DTI tractography

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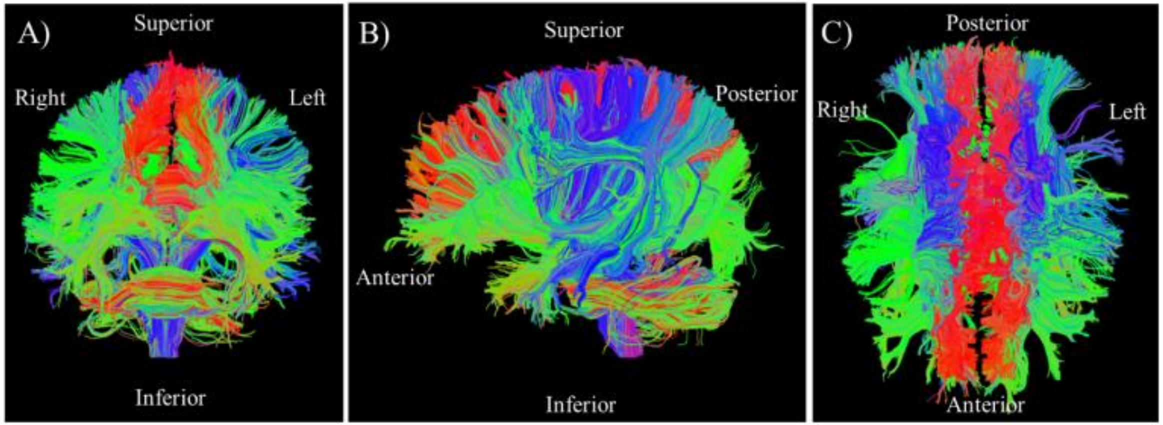
Tractography

- Tractography is the 3D reconstruction of “white matter” bundles from dMRI data.

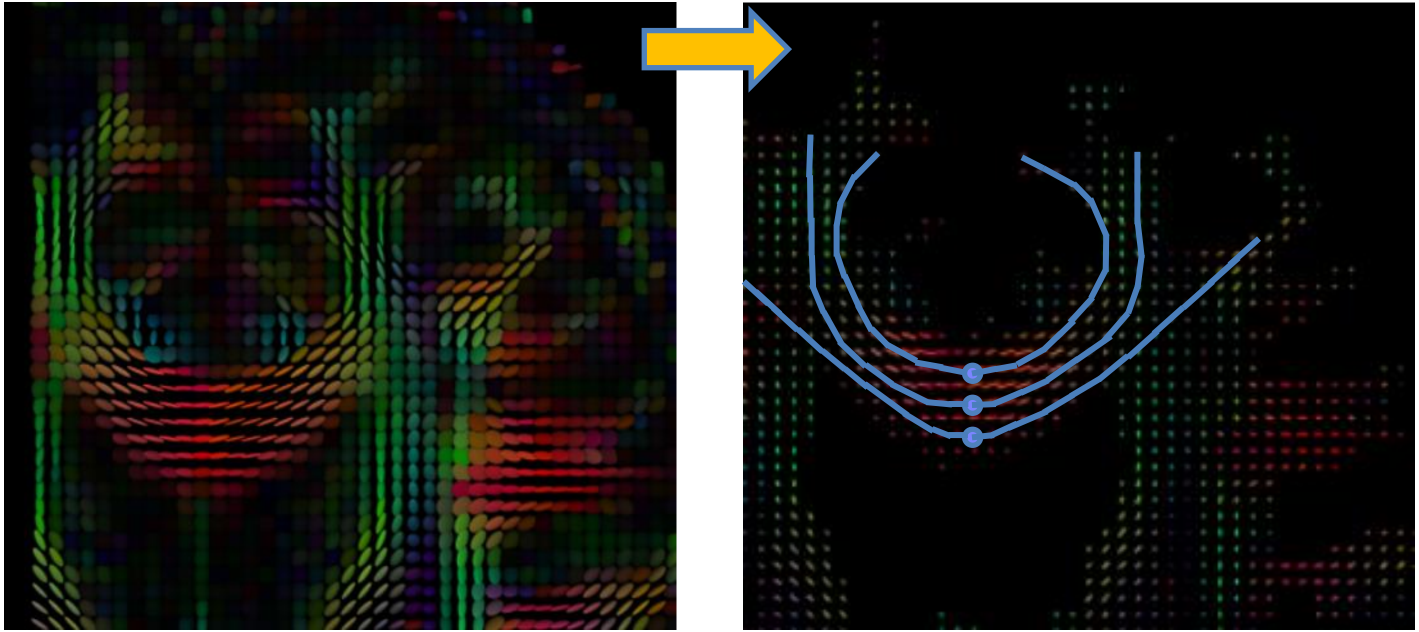


- In this workshops, two types of local tracking algorithms will be described:

1. Deterministic Tractography
2. Probabilistic Tractography

Deterministic Tractography

1. Extract directions from a given model



2. Define streamline starting points - seeds

3. Tracking stopping criterium (e.g.):

- Reaching out of brain voxels
- Reaching grey matter
- Reaching voxels with low FA
- Reaching voxels with discrepant directions

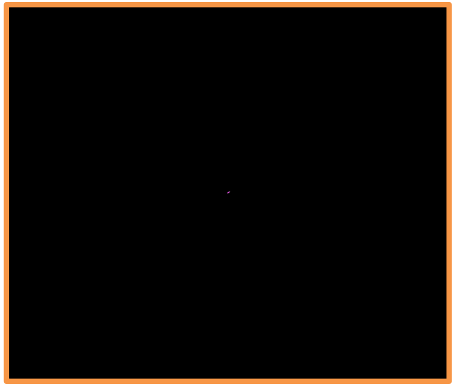
4. Pathways propagation algorithm

Resolved pathways does not correspond to “real” white matter fibres.
Pathways are also referred to as **streamlines**.

Probabilistic Tractography

- Probabilistic Tractography directions are sampled from orientation distribution functions (ODF)
  - ODF can be calculated from the displacement probability distribution

$$ODF(\boldsymbol{n}) \equiv \frac{1}{Z}\int_0^\infty P(s\boldsymbol{n},\Delta)\, s^2 ds$$

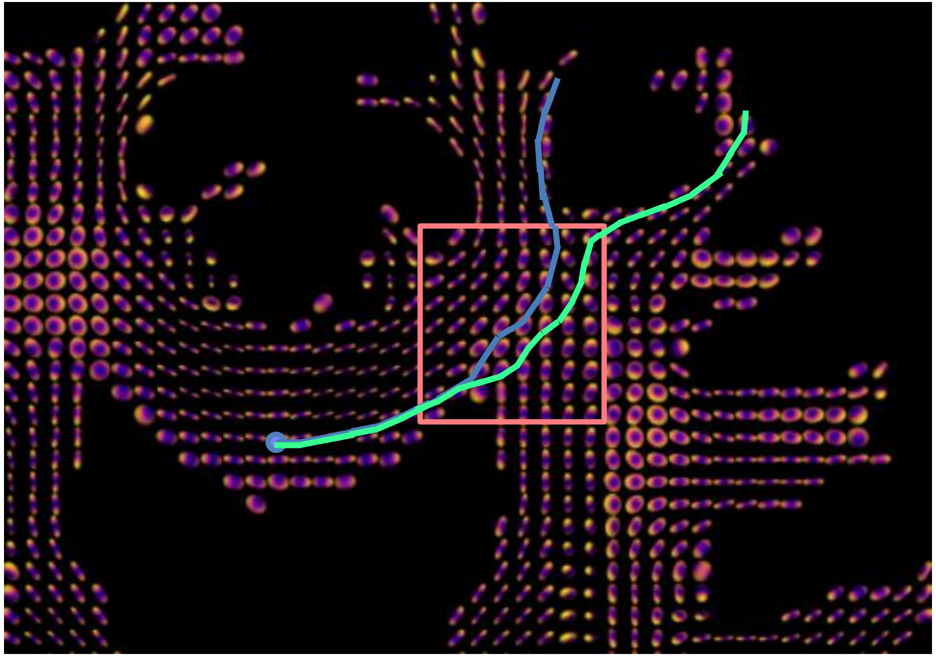


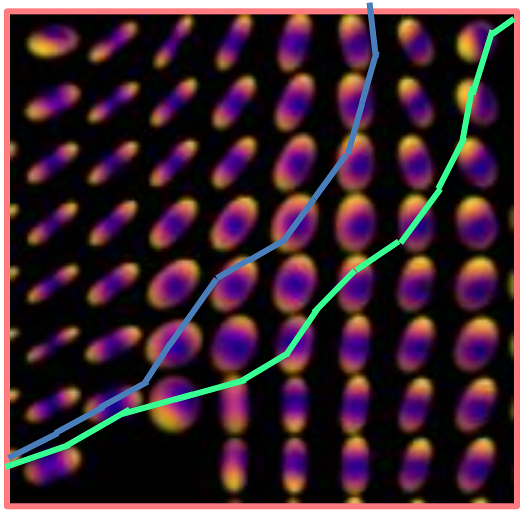
  - For DTI

$$ODF(\boldsymbol{n}) = \frac{1}{4\pi|\boldsymbol{D}|^{1/2}}\left(\frac{1}{\boldsymbol{n}^T\boldsymbol{D}^{-1}\boldsymbol{n}}\right)^{3/2}$$

Probabilistic Tractography

- Tractography is the 3D reconstruction of “white matter” bundles from dMRI data.





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High angular resolution diffusion imaging

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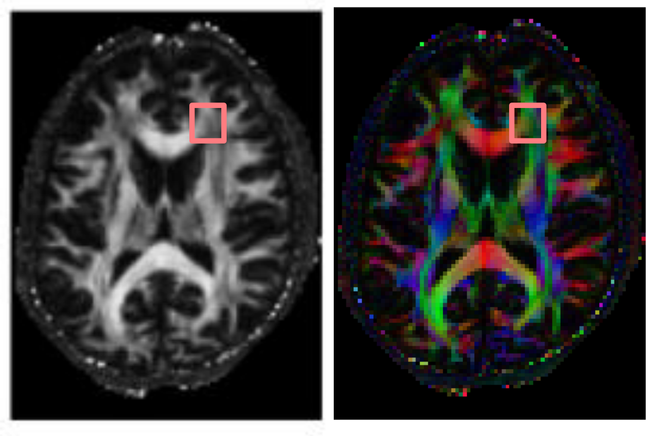
Propagator

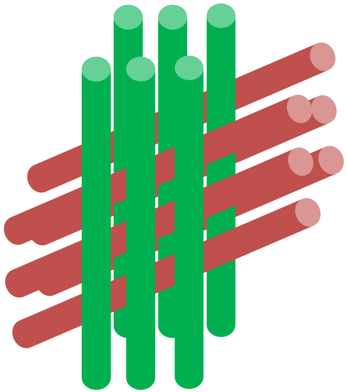
- DTI models dMRI signals as an 2[nd] order tensor which can be used to infer the main direction of well aligned structures.

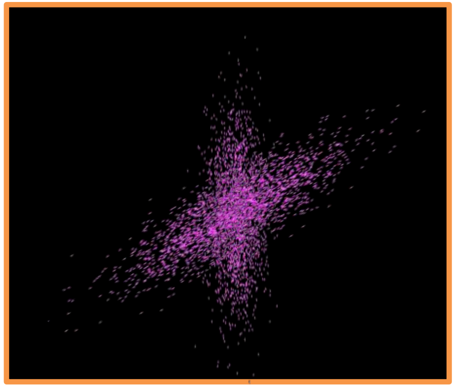
- DTI fails to represent the directionality of more complex structures

- The displacement probability distribution (**Propagator**), however, can provide more complete information of the direction of structures

Crossing fibre examples





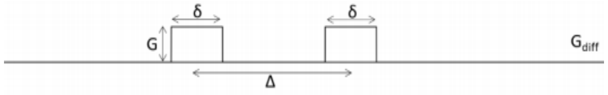


Diffusion Spectrum Imaging

- Diffusion Spectrum Imaging (DSI) is a model free approach to reconstruct the propagator

Wedeen et al. MRM 2005

Narrow pulse assumption ($\delta \ll \Delta$)



$$b = q^2\Delta$$

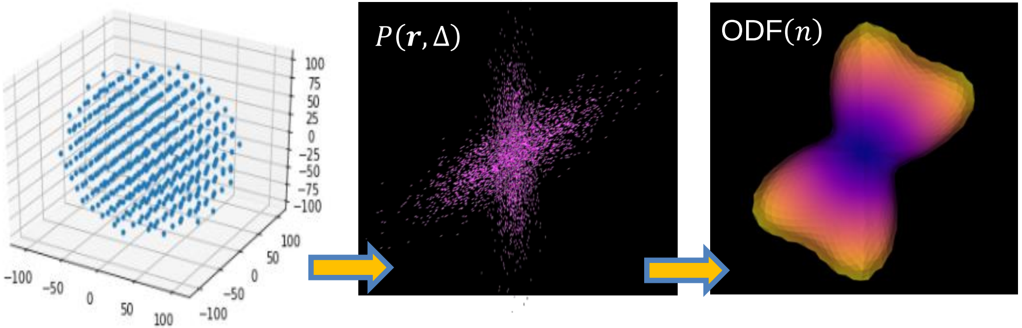
$$\frac{S(\boldsymbol{q},\Delta)}{S_0} = \int P(\boldsymbol{r},\Delta)\, e^{-2\pi i \boldsymbol{q}^T \boldsymbol{r}} d\boldsymbol{r}, \qquad \boldsymbol{q} = q\boldsymbol{n}$$

Fourier Transform

$$P(\boldsymbol{r},\Delta) = F\left(\frac{S(\boldsymbol{q},\Delta)}{S_0}\right)$$

$$ODF(\boldsymbol{n}) \equiv \frac{1}{Z}\int_0^{\infty} P(s\boldsymbol{n},\Delta)\, s^2 ds$$

- Propagator and ODF is calculated directly from signals sampled from different **q** vectors



- Requires a huge set of **q** vectors (long acquisition times),
- Requires the acquisition of high magnitudes of **q** (b-values not available in current clinical scanners)

High Angular Resolution Diffusion Imaging (HARDI)

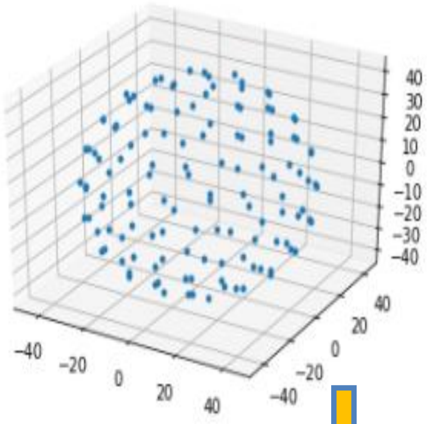
Tuch et al. MRM 2004

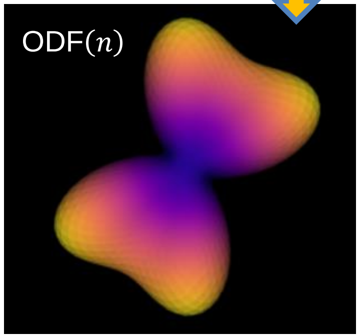
Aganj et al. MRM 2010

- Q-ball imaging was proposed to reconstruct the ODF from acquisition at single **q** vector magnitudes (single shell acquisitions)

$$P(\boldsymbol{r}, \Delta) = F\left(\frac{S(\boldsymbol{q}, \Delta)}{S_0}\right)$$

- The information of other **q** magnitudes is extrapolated based on model assumptions
  - E.g. assuming that along directions diffusion is Gaussian

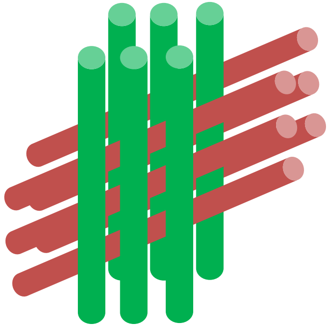


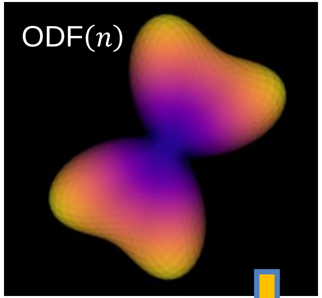


Constrained Spherical Deconvolution (CSD)

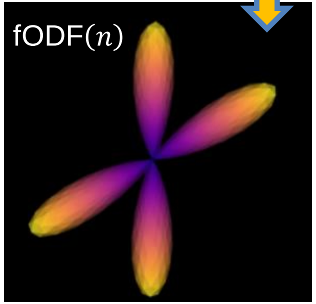
- Diffusion provides indirect inference of tissue properties.
  - ODF provides a smooth probability distribution of the direction of maximum diffusivity

- Constraint spherical deconvolution (CSD) was proposed to reconstruct the fibre ODF (fODF)



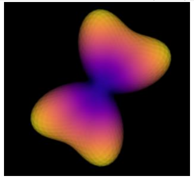


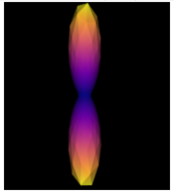
ODF deconvolution



$$\frac{S(b,\boldsymbol{n})}{S_0} = fODF(\boldsymbol{n}) \otimes K\,(b,\boldsymbol{n})$$

$$ODF(\boldsymbol{n}) = fODF(\boldsymbol{n}) \otimes R\,(\boldsymbol{n})$$





Tournier et al., 2004
Dell'Acqua et al. 2007
Descoteaux et al., 2009

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HARDI tractography

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HARDI Tractography

Deterministic and Probabilistic Tractography from HARDI can be performed in a similar way than DTI tractography

As DTI tractography it involves the following steps:

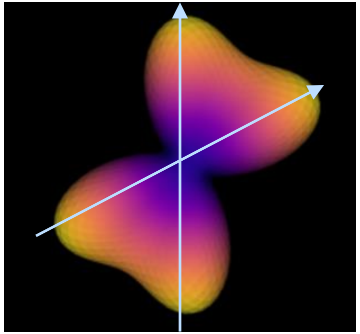
1. Direction generation.
   - For deterministic tracking, directions are extracted from the ODF/fODF peaks
   - For probabilistic tracking, directions are randomly sampled according to the ODF/fODF

2. Define streamline seeds

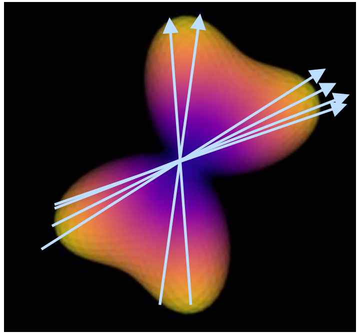
3. Tracking stopping criterium

4. Pathways propagation algorithm

Deterministic direction generator



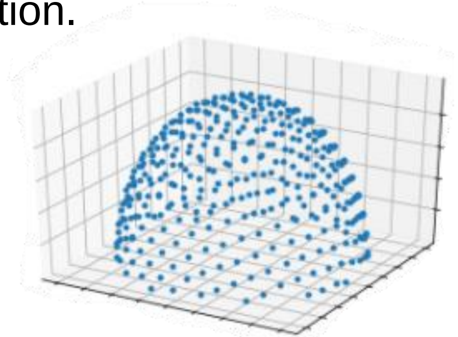
Probabilistic direction generator



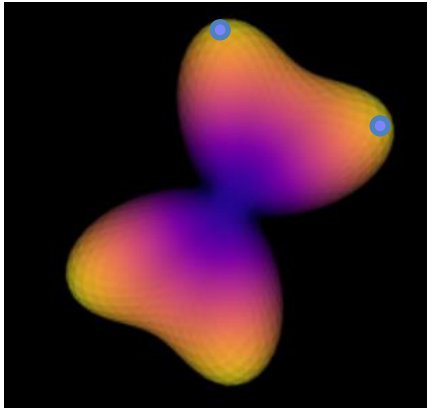
HARDI Tractography

Inputs of the algorithm to detect the maximum direction

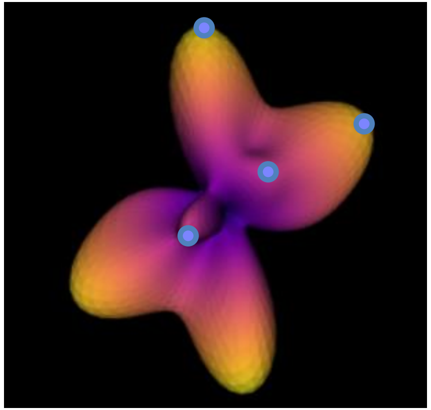
- **Sphere** - discrete directions for maximum evaluation.



- **Relative_peak_threshold –** threshold to remove small peaks that may be related to noise
- **min_separation_angle –** the minimum distance between peaks



Noisy ODF



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Pre-processing diffusion MRI data

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Pre-processing diffusion MRI data

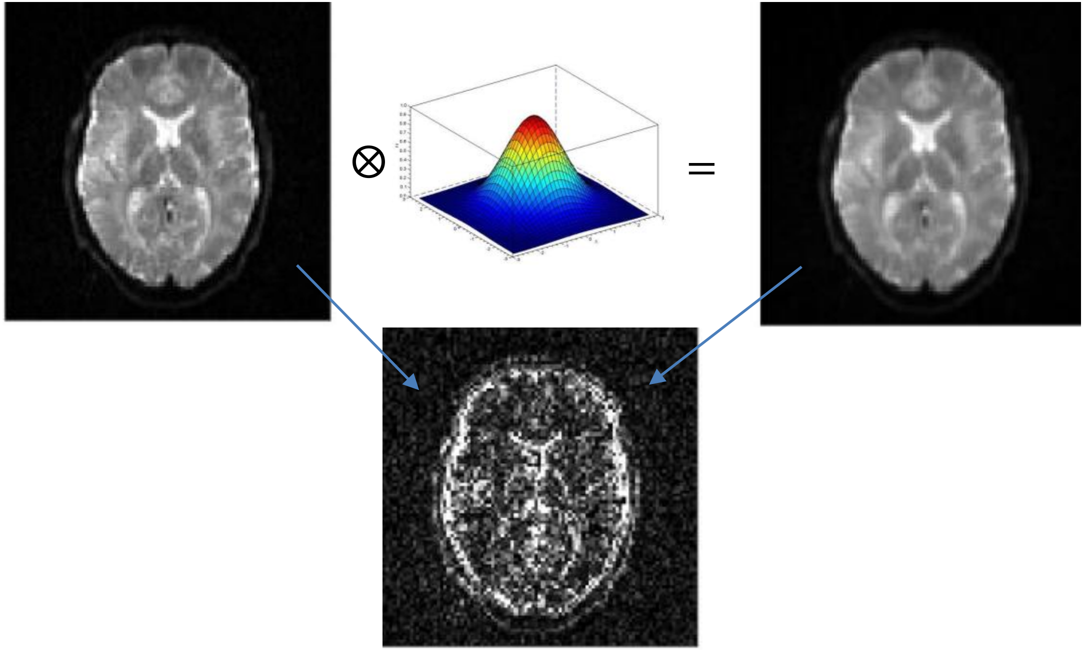
1. Denoising

2. Gibbs Artefact correction

3. Motion, B0 inhomogeneity, eddy currents

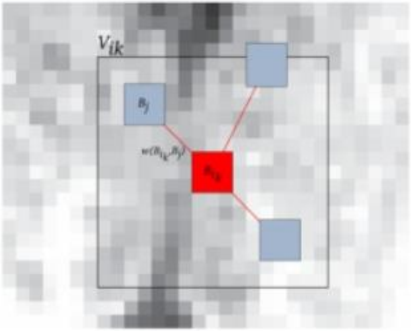
1. Denoising

- Diffusion MRI data suffers from low SNR
  - Diffusion gradient attenuation, long echo times
- Strategies to suppress noise artefacts
  - Gaussian Smoothing



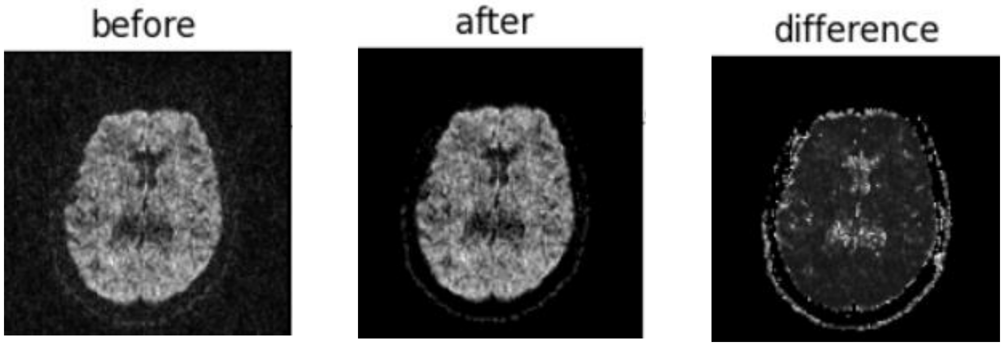
1. Denoising

- Diffusion MRI data suffers from low SNR
  - Diffusion gradient attenuation, long echo times
- Strategies to suppress noise artefacts
  - Gaussian Smoothing
  - Non-local means



Coupe et al., IEEE Trans Med Imaging 2008

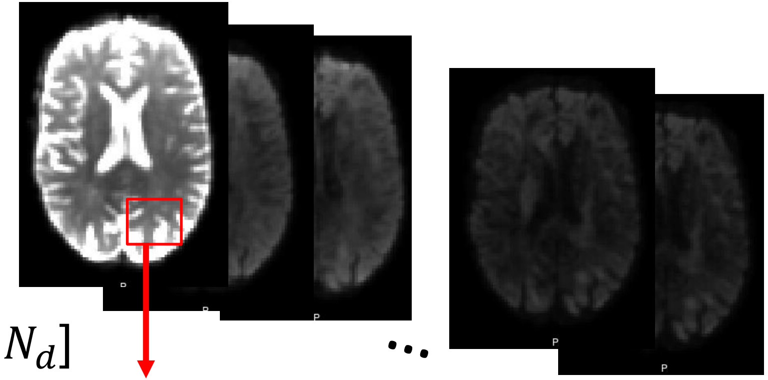
Coupe et al., IEEE Trans Med Imaging 2011



DIPY’s example: [example-denoise-gibbs]

1. Denoising

- Diffusion MRI data suffers from low SNR
  - Diffusion gradient attenuation, long echo times
- Strategies to suppress noise artefacts
  - Gaussian Smoothing
  - Non-local means
  - PCA denoising



$X \quad [N_v \times N_d]$

Manjón et al., 2013

Veraart et al., 2016

$$\frac{1}{N} X^T X = U \Lambda^2 U^T$$

1. Denoising

- Diffusion MRI data suffers from low SNR
  - Diffusion gradient attenuation, long echo times
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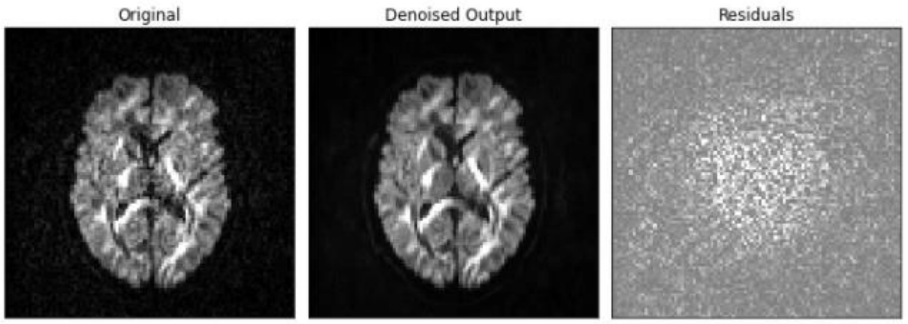
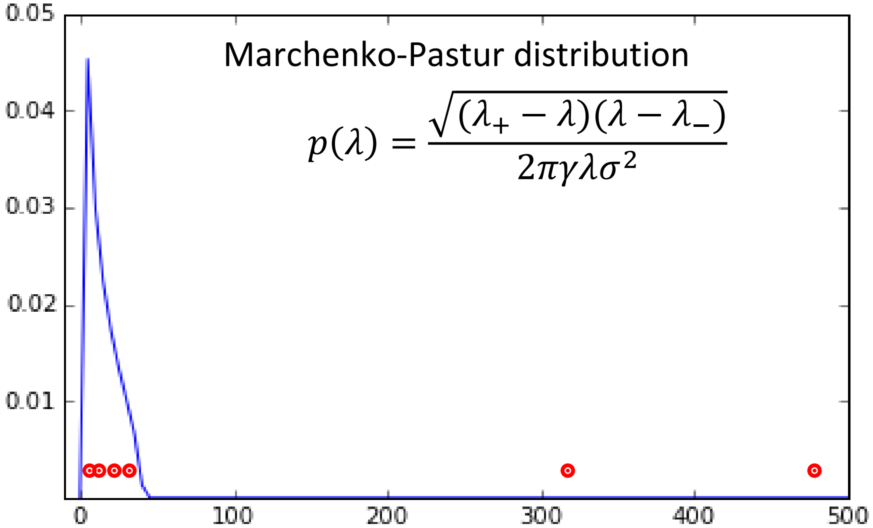
  - Non-local means
  - PCA denoising

Manjón et al., 2013

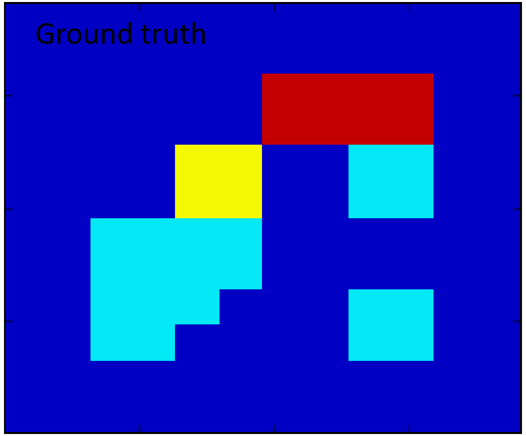
Veraart et al., 2016

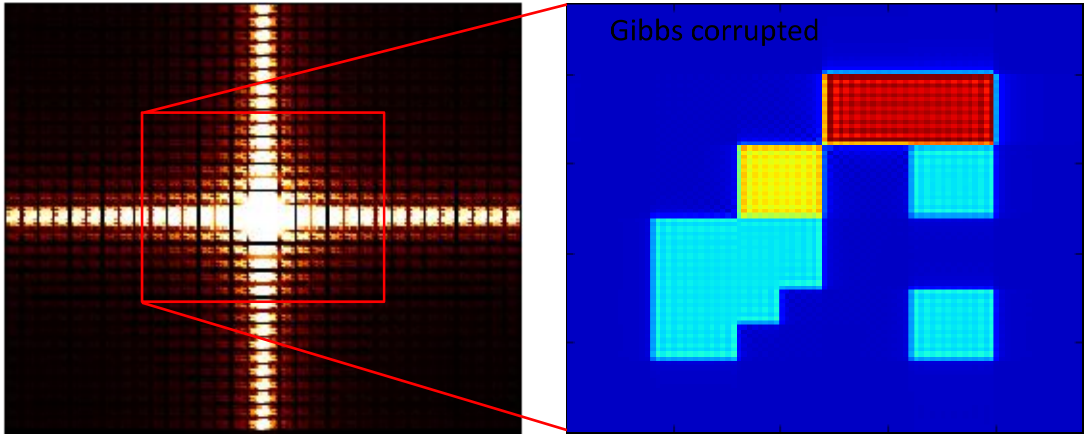


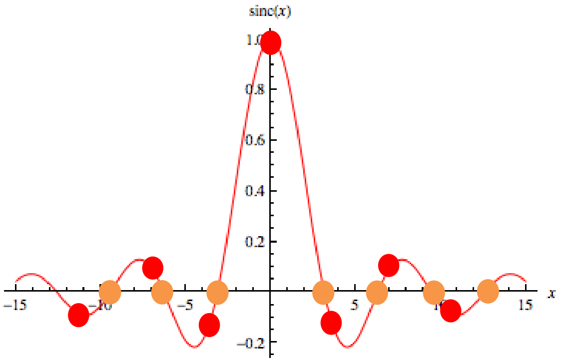


2. Gibbs Artefacts

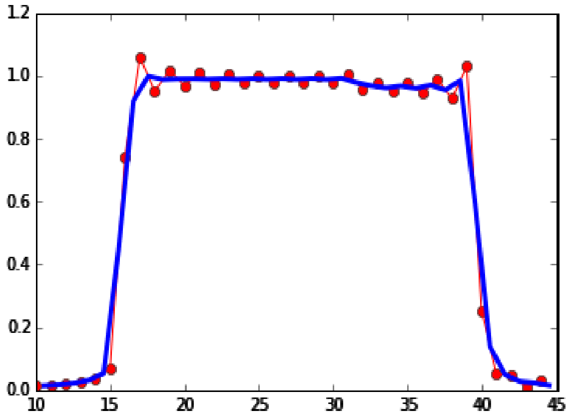
Kellner et al., 2016

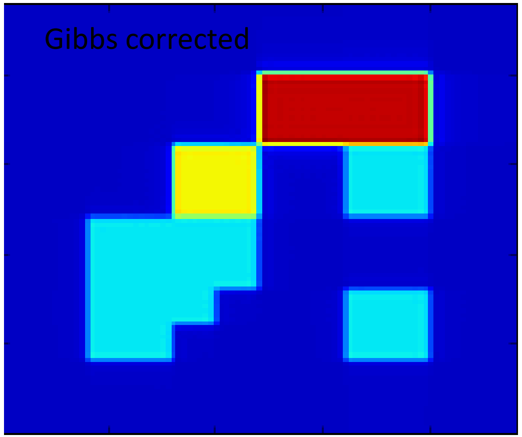






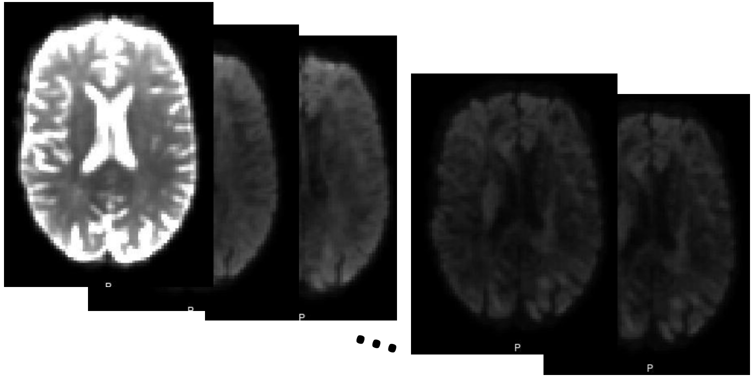
$$I(x - x_o) = FT^{-1}\{c.e^{-2ikx_0/N}\}$$





3. Physiological Noise, B0 inhomogeneities, eddy currents

- Diffusion MRI acquisitions involves the acquisition of several images
  - Motion Misalignments



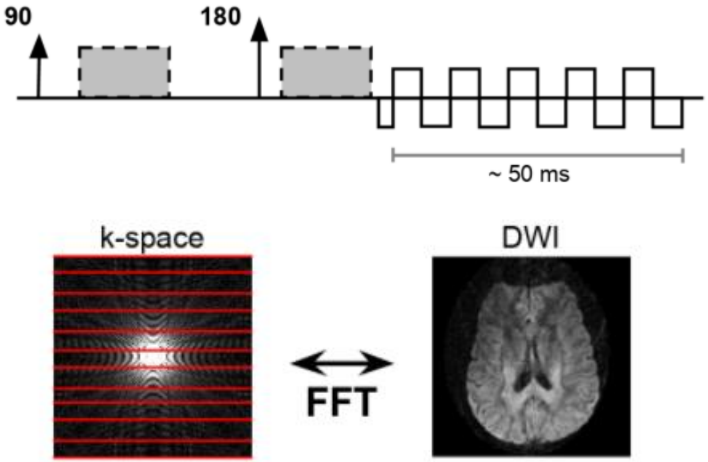
- Image Registration
  - See for example the dipy tutorials:

[Affine Registration in 3D]

[Symmetric Diffeomorphic Registration in 3D]

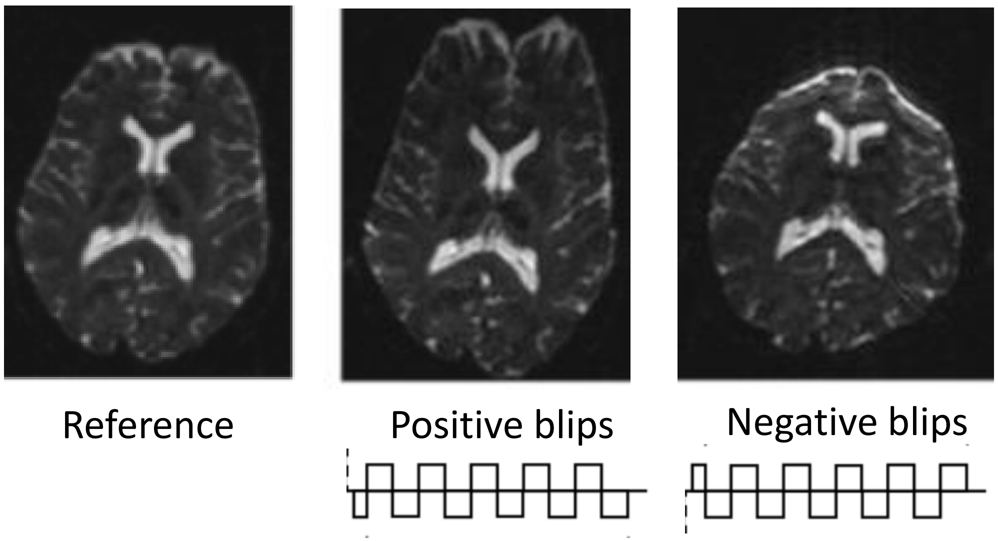
3. Physiological Noise, B0 inhomogeneities, eddy currents

- Diffusion captures information of water displacements in the order of the microns - Head motion can happen in the order of the millimetres
- Due to its speed, the most commonly used sequence for dMRI is EPI (Echo Planar Imaging).



Turner et al., Radiology 1990

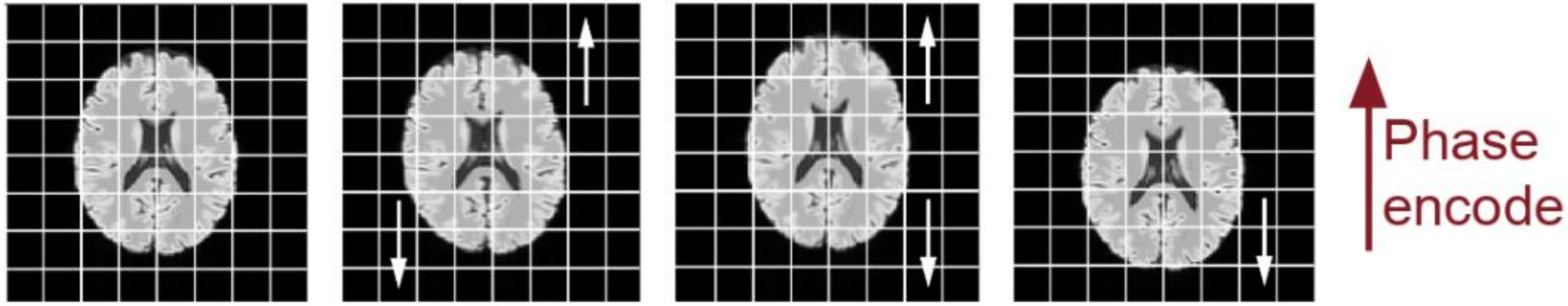
B0 inhomogeneities



3. Physiological Noise, B0 inhomogeneities, eddy currents

- Switching ON/OFF of the strong diffusion gradients induces eddy currents

- Eddy currents overlap with imaging gradients producing geometric distortions



a) Reference

b) Shearing (eddy currents in readount)

c) Scalling (eddy currents in phase encoding)

d) Scalling (eddy currents in slice-select)

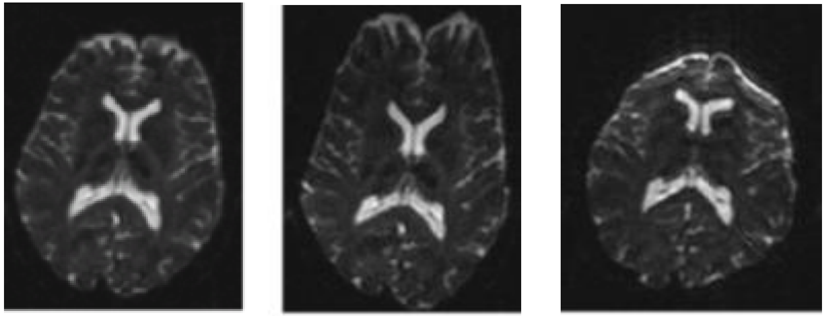
Jezzard et al. MRM 1998

3. Physiological Noise, B0 inhomogeneities, eddy currents

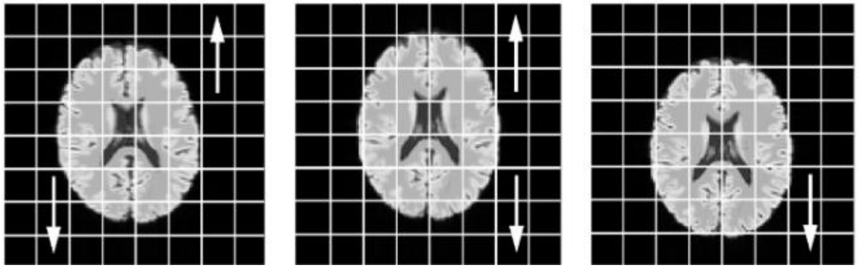
- Advance strategies to simulataneously correct motion, B0 inhomogeneities and eddy currents are available in [FSL]

- If you are interested in using these tools give a look to FSL documentation before acquiring your data

B0 inhomogeneities



Eddy currents



Jesper et al. Neuroimage 2015

Champalimaud
Foundation

Quantifying tissue microstructure

Rafael Neto Henriques

Champalimaud Research, Champalimaud Centre for the Unknown, Lisbon, PT

Diffusion MRI modelling

1. Phenomenological model (Signal Representations)

2. Mechanistic Model (Microstructural Models)

Received: 28 June 2017 | Revised: 22 December 2017 | Accepted: 1 January 2018

DOI: 10.1002/mrm.27101

REVIEW

Magnetic Resonance in Medicine

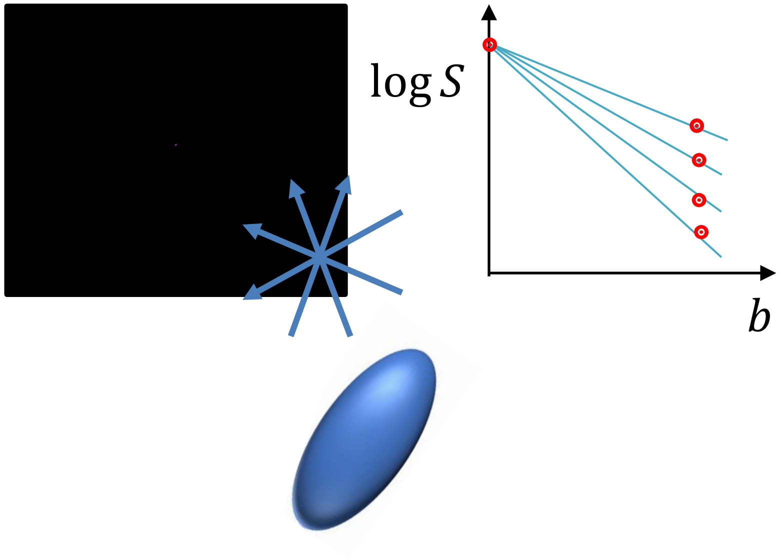
On modeling

Dmitry S. Novikov[1] | Valerij G. Kiselev[2] | Sune N. Jespersen[3,4]

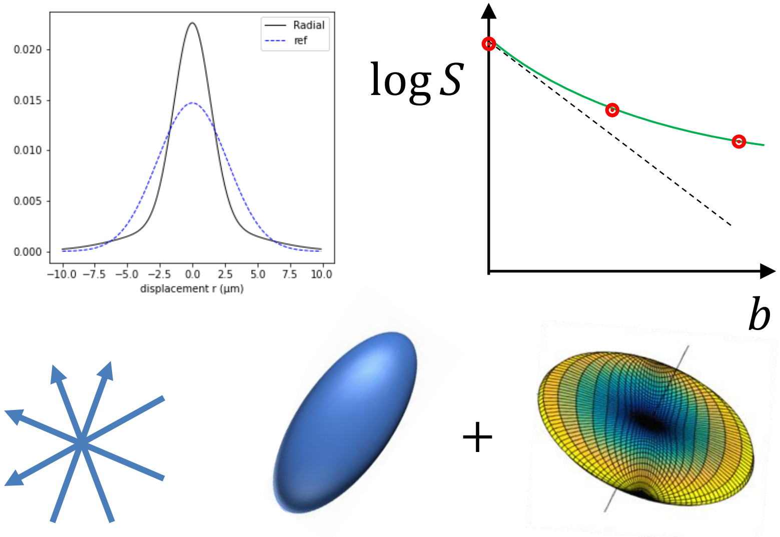
Signal Representations

1. Signal representations quantify diffusion properties without considering its biological underpinnings, e.g.

DTI quantifies diffusion anisotropy from signals for different directions



DKI quantifies anisotropy and non-Gaussian diffusion from signals for different directions and b-values

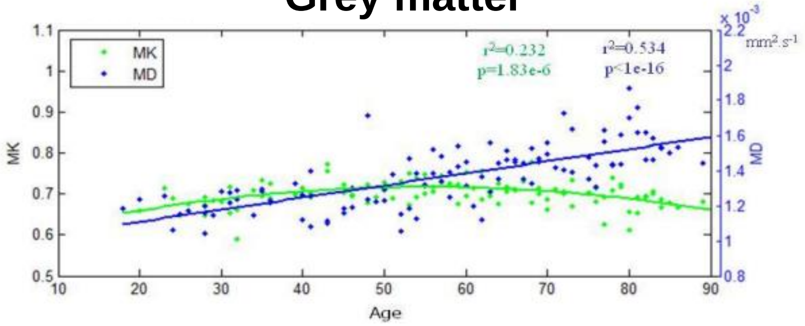


Signal Representations

- Advantages of measuring non-Gaussian diffusion

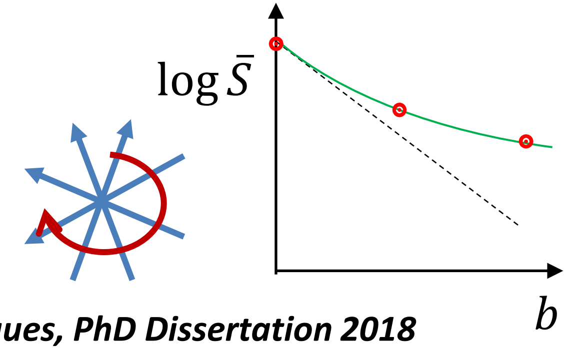
1. Non-Gaussian properties can be used to study microstructural alterations even in regions with low anisotropy (e.g. grey matter)

Grey matter



Henriques, Master Dissertation 2012

2. Non-Gaussian properties can be extracted even for signals averaged across directions

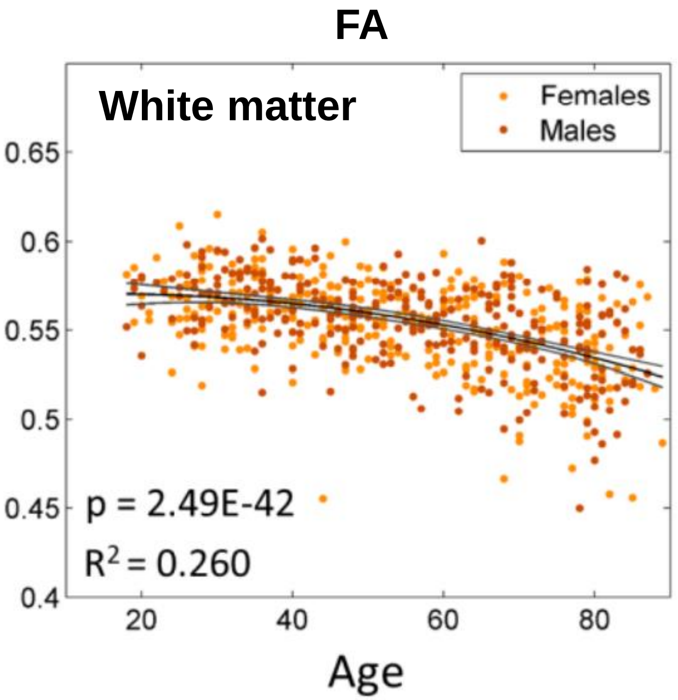


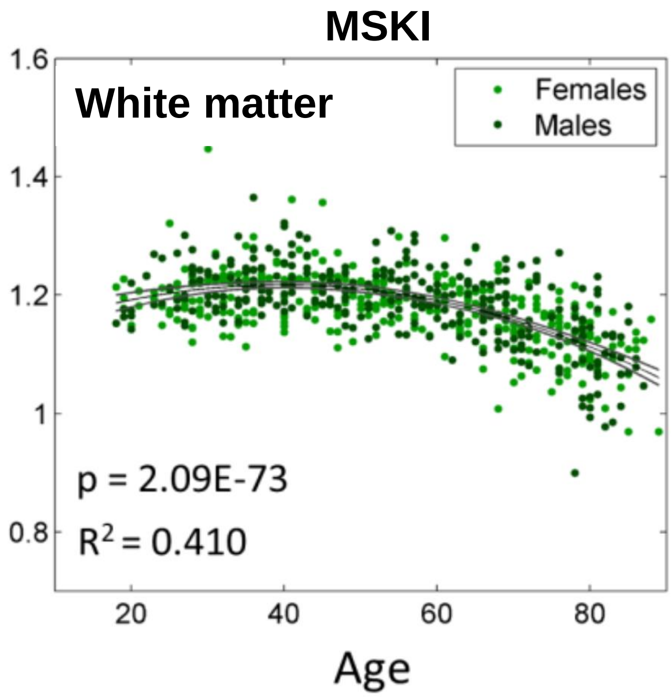
Henriques, PhD Dissertation 2018

$$\mathrm{MSKI}_1 = \mathrm{MSKI}_2$$

– Study microstructural alterations independent to changes on tissue dispersion/crossing

Signal Representations





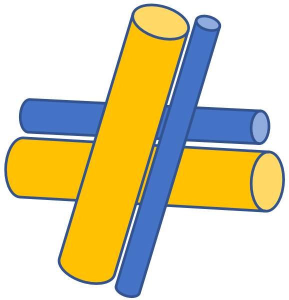
Henriques, PhD Dissertation 2018

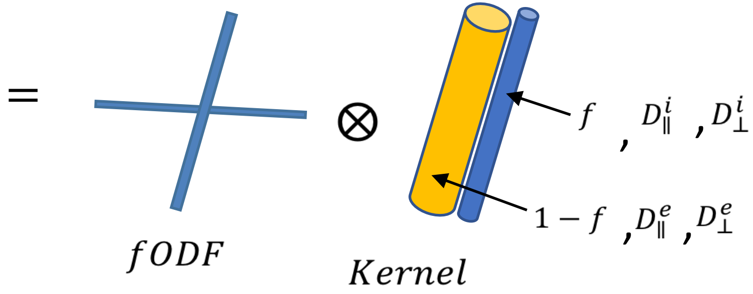
Microstructural Models

2. Microstructural models uses biophysical models to directly estimate microstructural properties

- IVIM
- Stanisz's Nerve Model
- Ball & Stick
- CHARMED
- Neurite Density Model
- AxCaliber / Active Ax
- NODDI
- WMTI
- VERDICT
- LEMONADE
- TEdDI
- SMT
- SMT2
- Fiber-ball imaging
- fw-DTI

$$S(b,\mathbf{n}) = f\sum_{i=1}^{N_f} e^{-b\mathbf{n}\mathbf{D}_{int}(\mathbf{d}_i)\mathbf{n}^T} + (1-f)\sum_{i=1}^{N_f} e^{-b\mathbf{n}\mathbf{D}_{ext}(\mathbf{d}_i)\mathbf{n}^T}$$





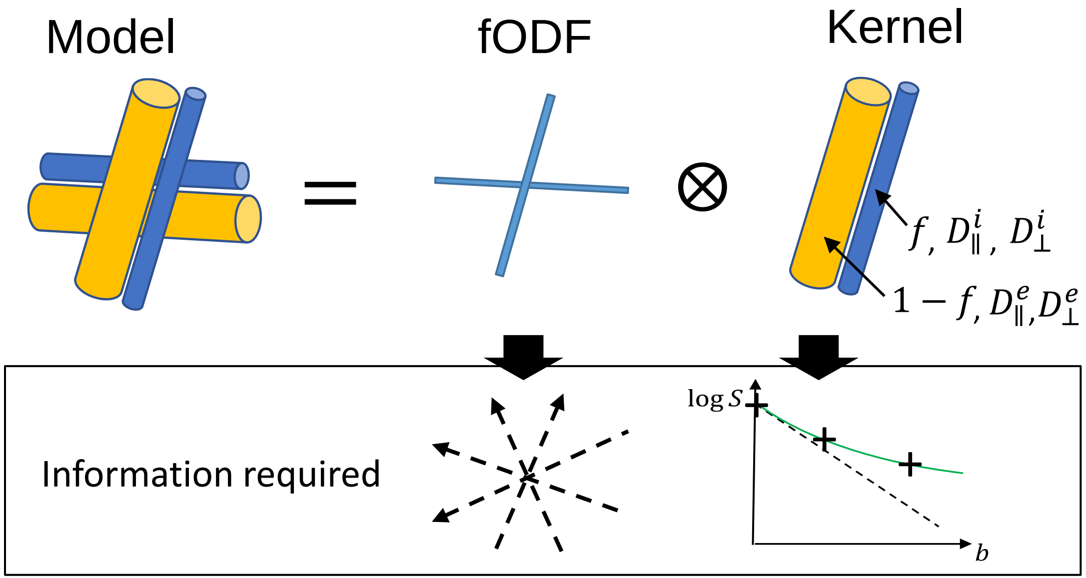
Jespersen et al., NeuroImage 2007

Most of techniques corresponds to the same models!

Basically they are just a different set of Constraints!

Microstructural Models

The number of parameter on models is limited to the information provided by dMRI data - **degrees of freedom (DOF)**



To decrease the number of fitted parameters assumptions and constraints are required

Microstructural Models

Example of Microstructural Models:

1. Neurite orientation dispersion and density model (NODDI)
2. Spherical Mean Technique (SMT)
3. White Matter integrity Model (WMTI)
4. Free water Diffusion Tensor Imaging (fwDTI)

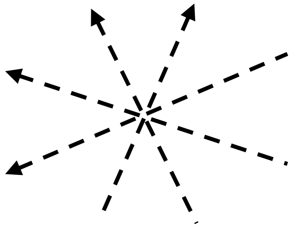
Microstructural Models

1. Neurite orientation dispersion and density model (NODDI)

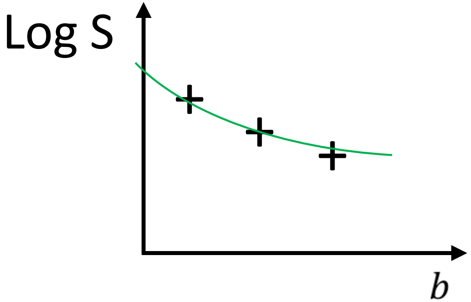
Zhang et. al., NeuroImage. 2012

DOF

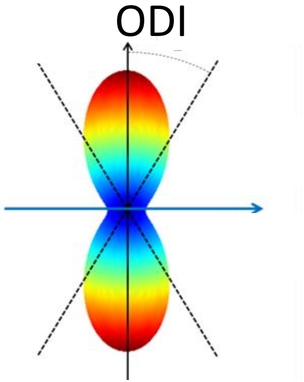
Multiple - directions



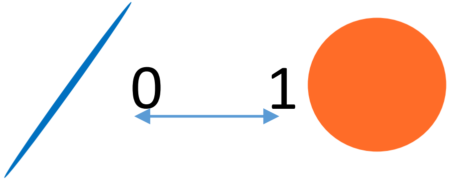
Multiple -bvalues



$fODF$ = Watson

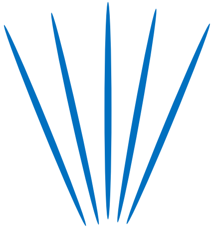


Orientation dispersion index (ODI)



$Kernel$

Intra-cellular



$f \times (1 - f_w)$

$D_{\parallel}^{i} = 1.7 \mu m^2/ms$

$D_{\perp}^{i} = 0$

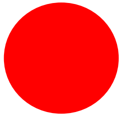
Extra-cellular

$(1 - f) \times (1 - f_w)$

$D_{\parallel}^{e}, D_{\perp}^{e} = F(D_{\parallel}^{i}, f, ODI)$

Tortuosity Constraint

Free-water



f_w $D_w = 3\ \mu m^2/ms$

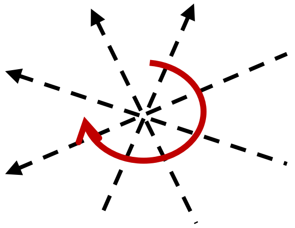
Microstructural Models

2. Spherical Mean Technique (2 compartmental Model)

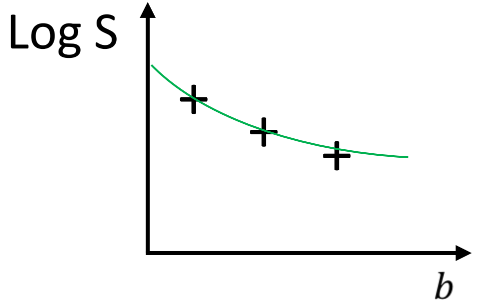
Kaden et. al., NeuroImage. 2016

DOF

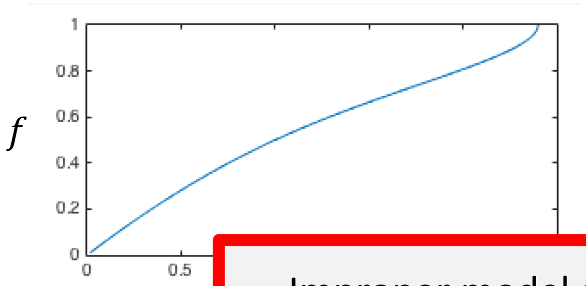
Multiple - directions

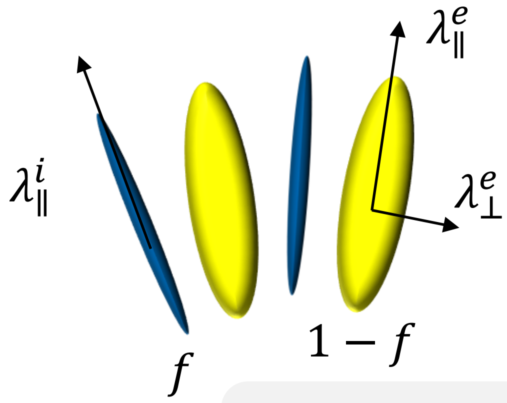


Multiple -bvalues



Signals are averaged so that kernel parameters are estimated independently from the fODF

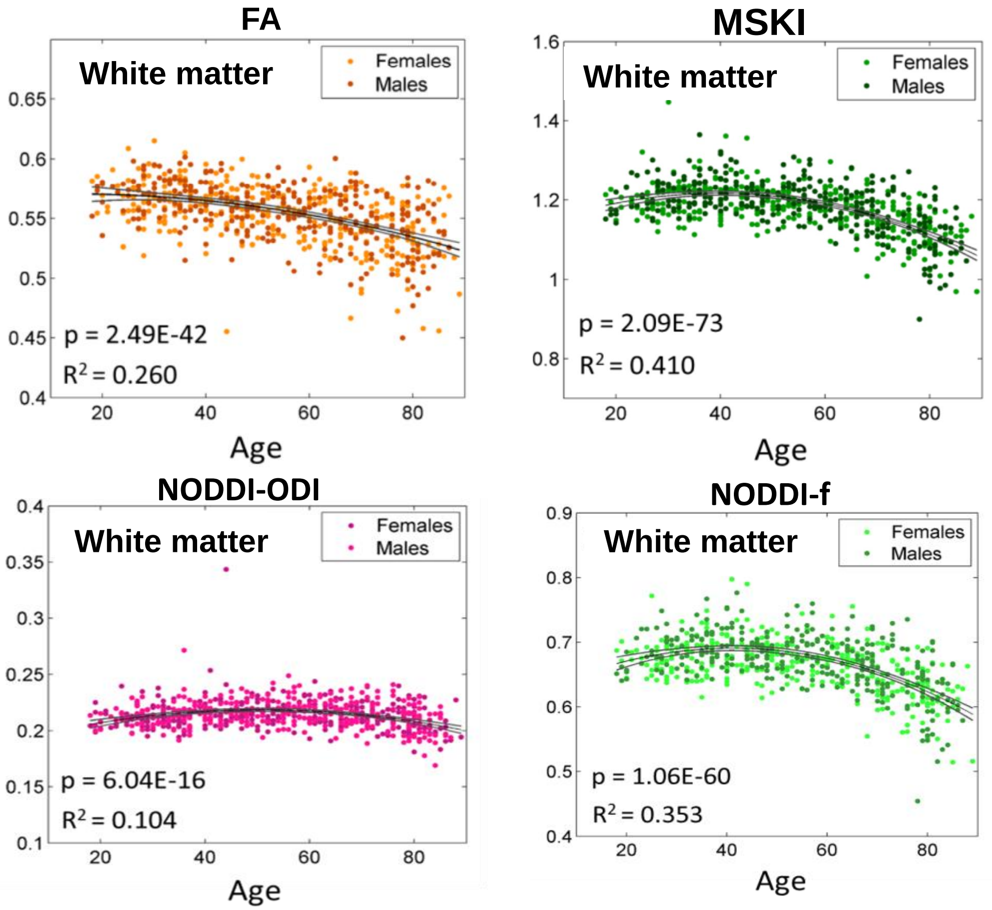




$$\lambda_{\parallel}^{e} = \lambda_{\parallel}^{i} = \lambda$$
$$\lambda_{\perp}^{e} = (1-f)\lambda$$

Improper model assumptions might compromise specificity!

Microstructural Models



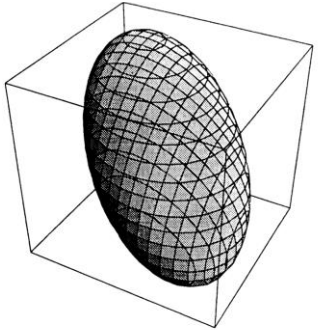
Henriques, PhD Thesis 2018

Microstructural Models

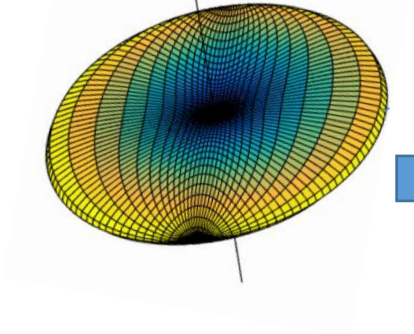
3. White Matter Tract Integrity (WMTI) Model

Fieremans et. al., NeuroImage. 2011

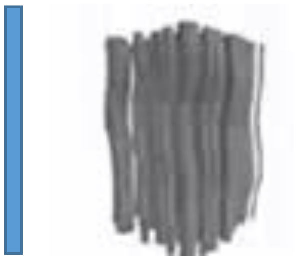
Diffusion Tensor



Diffusion Tensor



$fODF$



DOF

AD – Axial Diffusivity

RD – Radial Diffusivity

AK – Axial Kurtosis

RK – Radial Kurtosis

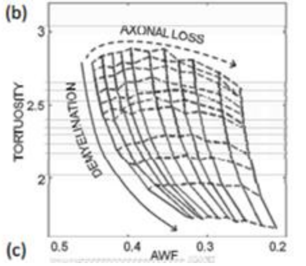
$Kernel$

Intra-cellular

f

$D_{\parallel}^{i}$

$D_{\perp}^{i} = 0$



Fieremans et al., ISMRM 2012

Extra-cellular

$(1-f)$

$D_{\perp}^{e}$

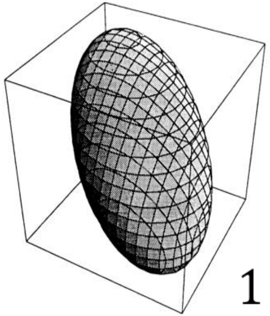
$D_{\parallel}^{e} > D_{\parallel}^{i}$

$tort = D_{\parallel}^{e}/D_{\perp}^{e}$

Microstructural Models

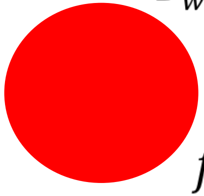
4. Free water DTI

Uses microstructural model components to resolve confounding sources of signal representation models



$1 - f_w$

$D_w = 3\ \mu m^2/ms$



f_w

Diffusion Tensor **+ Free water**

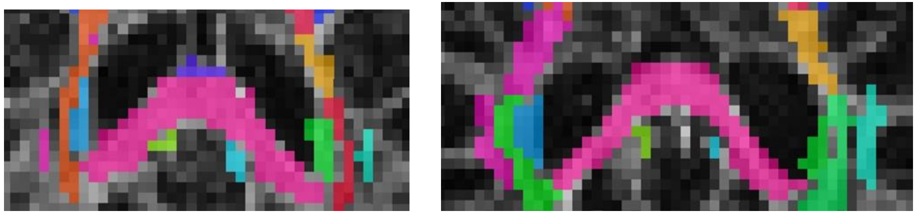
AD – Axial Diffusivity

RD – Radial Diffusivity

MD – Mean Diffusivity

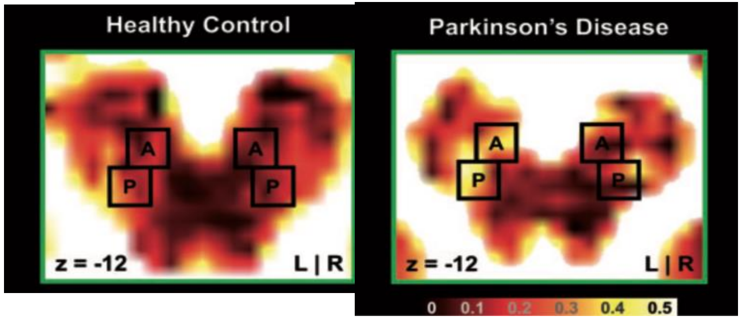
FA – Fractional Anisotropy

1) To remove partial volume effects



30 70

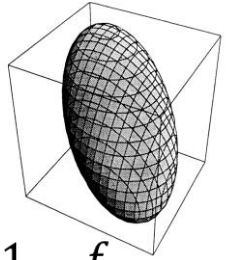
2) Free-water as a more specific measure



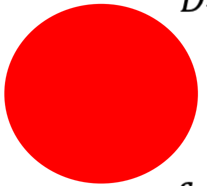
Ofori et al. Brain 2015

Microstructural Models

4. Free water DTI – single shell fitting



$1 - f_w$



$D_w = 3\ \mu m^2/ms$

f_w

Marc Golub

Rita Nunes

TÉCNICO LISBOA

LaSEEB Evolutionary Systems Biomedical Engineering

Magnetic Resonance in Medicine 62:717–730 (2009)

Free Water Elimination and Mapping from Diffusion MRI

Ofer Pasternak,[1*] Nir Sochen,[2] Yaniv Gur,[2] Nathan Intrator,[1] and Yaniv Assaf[3,4]

- Spatial regularization
- Initial Solution

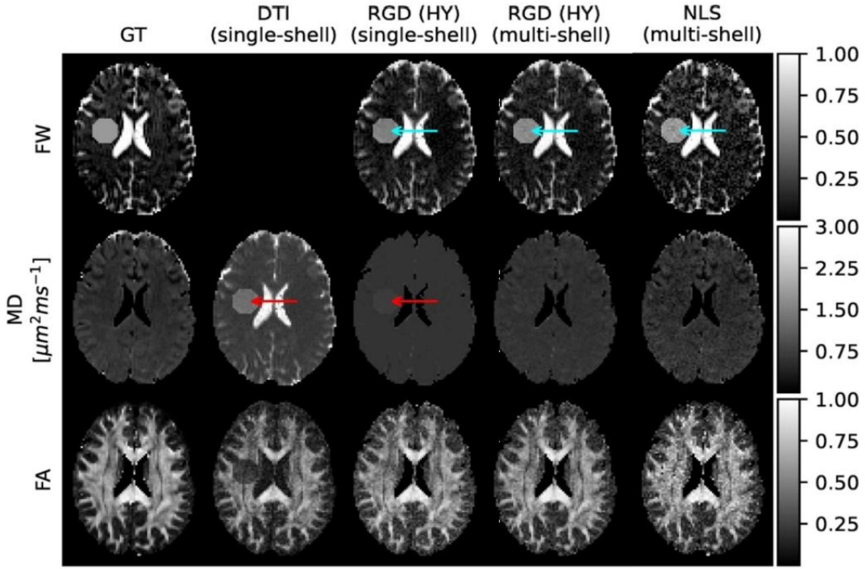
Microstructural Models

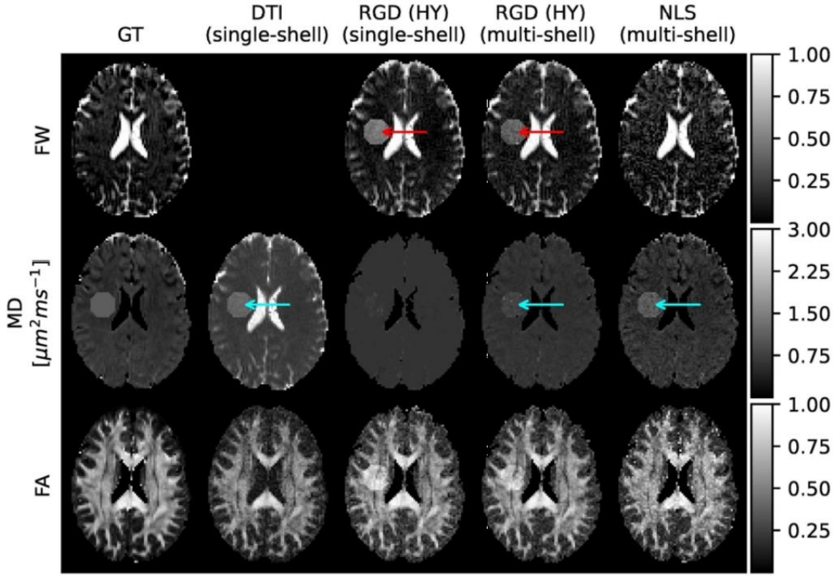
4. Free water DTI – single shell fitting

Golub et al. MRM 2020 (accepted)

Free water DTI estimates from single b-value data might seem plausible but must be interpreted with care

Marc Golub[1], Rafael Neto Henriques[2 †], Rita G. Nunes[1 †]

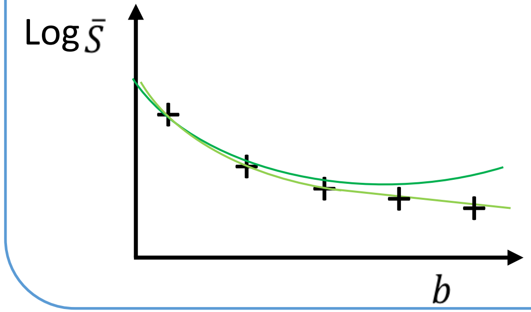




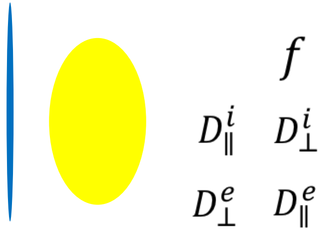
Microstructural Models

RotInv/LEMONADE

Novikov et. al., NeuroImage. 2018

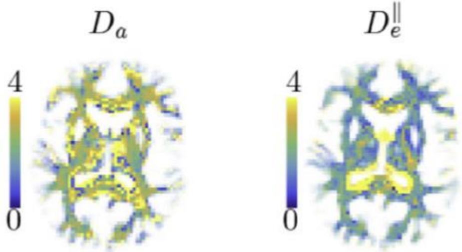


Expansion of WMTI for higher b-values



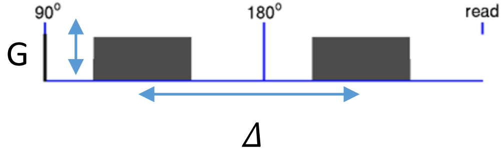
TEdDI

Different echo times to improve model's fitting landscape

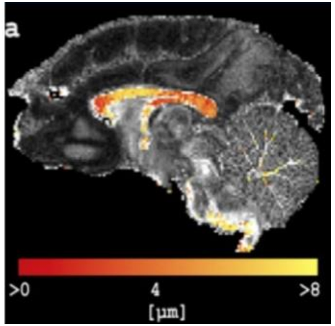


Veraart et. al., NeuroImage. 2018

AxCaliber / ActiveAx



Different diffusion times Δ to measure compartment sizes



Alexander et. al., NeuroImage. 2010

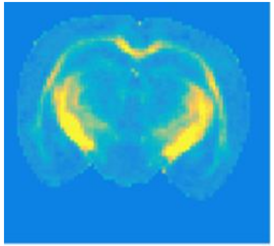
Non-Conventional sequences

- Double diffusion encoding

  Mitra Phys Rev B 1995

- Q-trajectory encoding

  Lasič et al. Front. Phys. 2014



Champalimaud Foundation

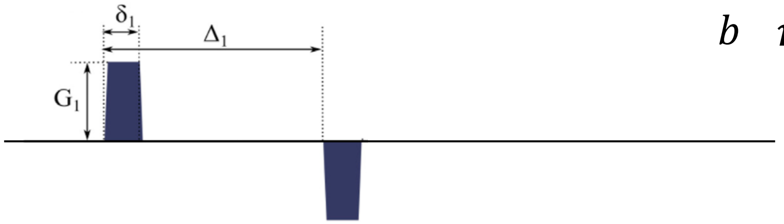
Future directions

Rafael Neto Henriques

Champalimaud Research, Champalimaud Centre for the Unknown, Lisbon, PT

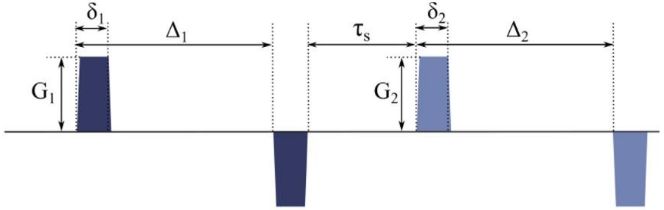
Advanced diffusion sequences

Single diffusion encoding (SDE)



$b \quad \boldsymbol{n}$

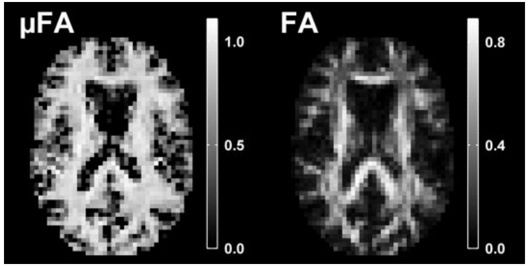
Double diffusion encoding (DDE)



$b_1 \, \boldsymbol{n}_1$

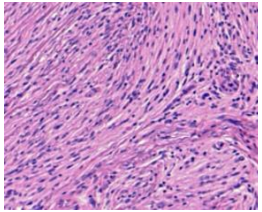
$b_2 \, \boldsymbol{n}_2$

Microscopic Fractional Anisotropy (μFA)

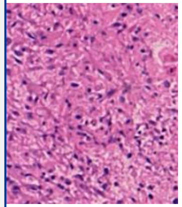


Shemesh & Cory MRM 2011

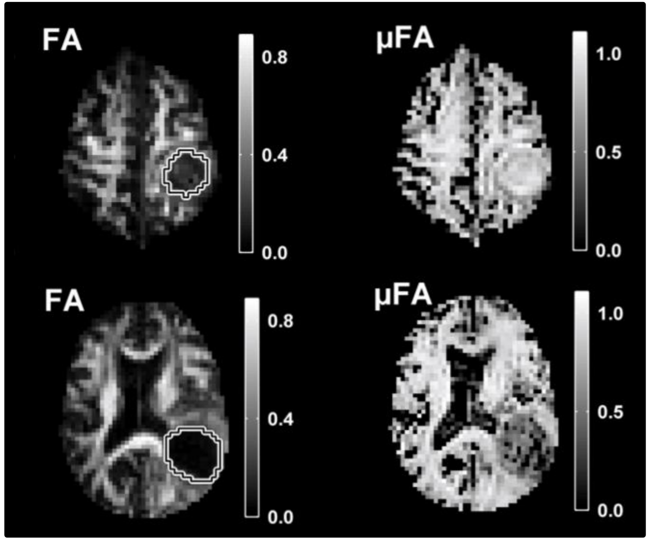
Szczepankiewicz et al., NeuroImage 2015



ingioma



blastoma



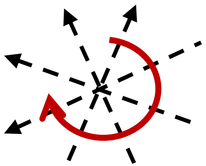
Szczepankiewicz et al., NeuroImage 2016

Tensor-valued diffusion MRI in under 3 minutes: an initial survey of microscopic anisotropy and tissue heterogeneity in intracranial tumors

Nilsson et al. MRM 2019

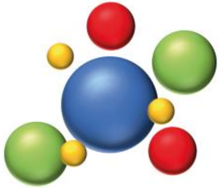
Advanced diffusion sequences

Single diffusion encoding



Sources of non-Gaussian diffusion

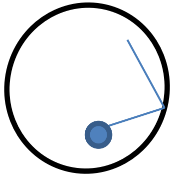
Variance in Diffusivities

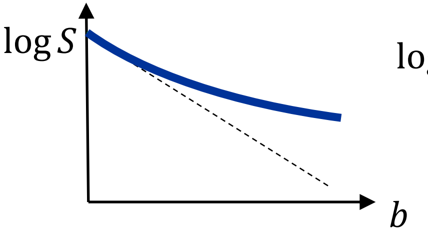


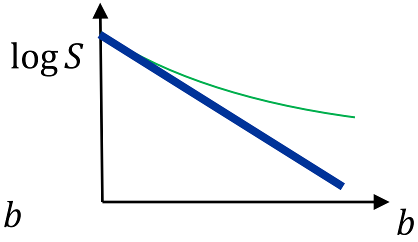
Isotropic

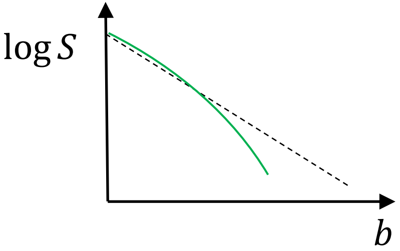
Anisotropic

Restricted diffusion/
Time Dependence

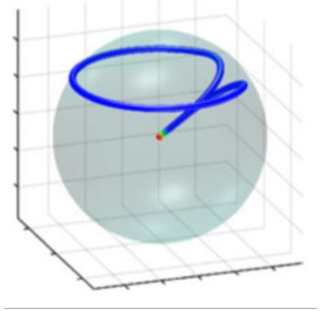


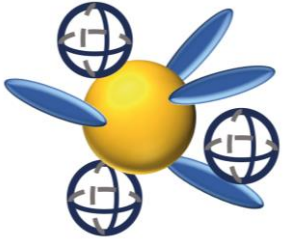


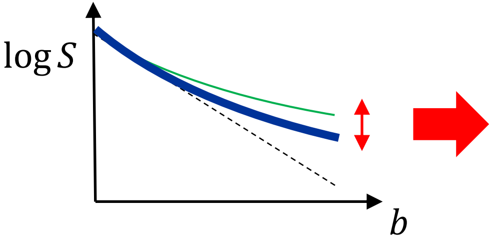


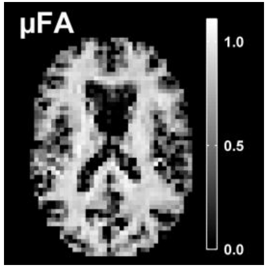


Isotropic diffusion Encoding









Lasič et al. Front. Phys. 2014

Westin et al., 2016

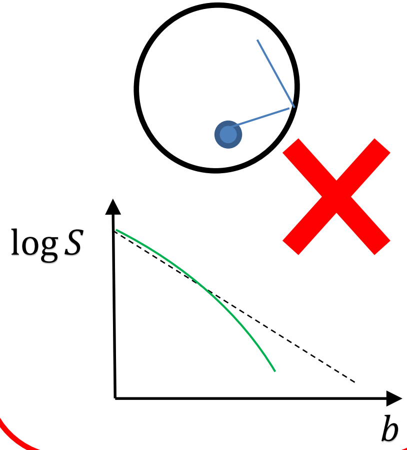
Advanced diffusion sequences

Single diffusion encoding

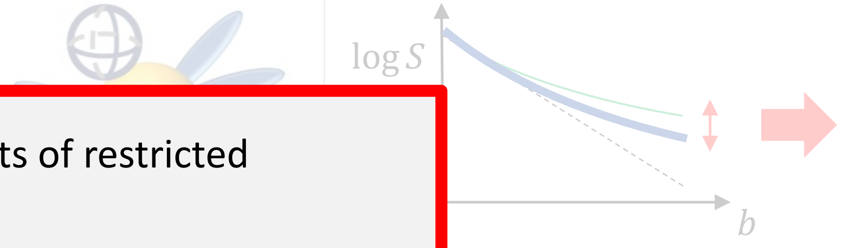
Sources of non-Gaussian diffusion

Variance in Diffusivities

Restricted diffusion/
Time Dependence



Isotropic diffusion Encoding



IDE does not consider effects of restricted diffusion/time dependence

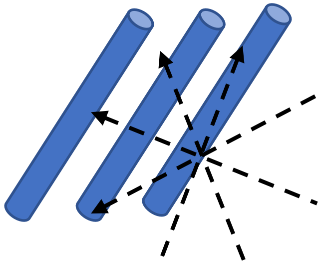
Correlation Tensor Imaging

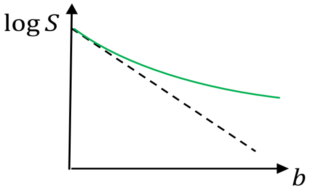
CTI is based on the cumulant expansion of DDE signals

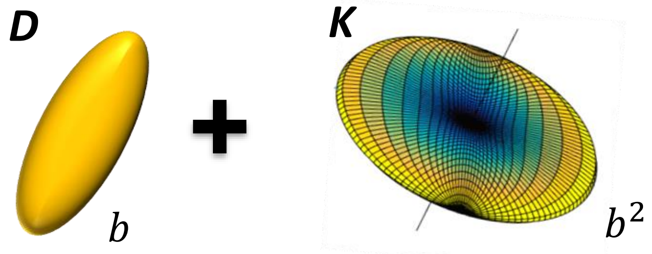
SDE

$$\log S = -bD + \frac{1}{6}b^2 D^2 K$$

Jensen et al., MRM 2005





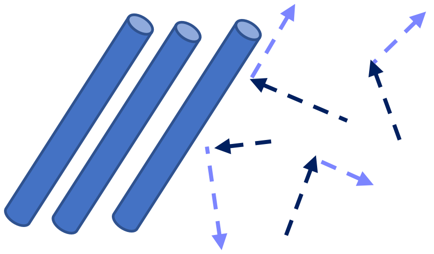


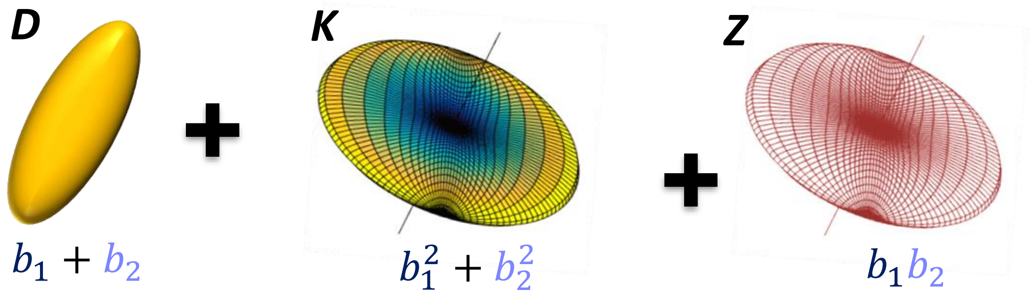
Henriques et al., NeuroImage 2015

DDE

$$\log S = -(b_1 + b_2)D + \frac{1}{6}(b_1^2 + b_2^2)D^2 K + b_1 b_2 D^2 Z$$

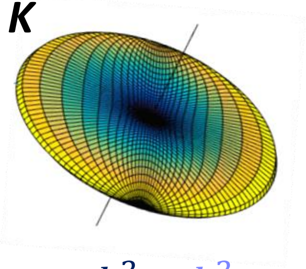
Jespersen, NMR Biomed 2011





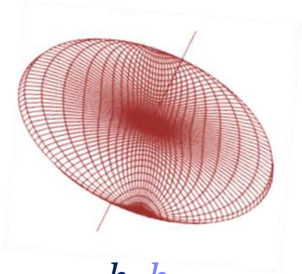
Correlation Tensor Imaging

K



$b_1^2 + b_2^2$

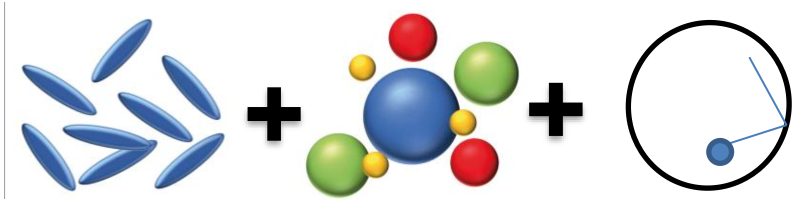
Z



$b_1 b_2$

anisotropic variance | isotropic variance | Restricted Diffusion

K_T

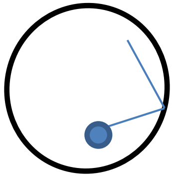


K_{aniso}

,

K_{iso}

$$K_{intra} = K_T - K_{aniso} - K_{iso}$$



Jespersen, NMR Biomed 2013

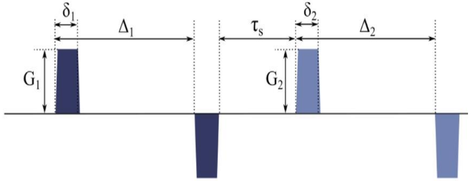
Westin CF et al. Neuroimage. 2016

Henriques, arXiv 2019

Correlation Tensor Imaging

- 16.4T Aeon
- DDE experiments:
  - Δ=13ms, t =13ms, δ=1.5ms
  - TR = 2200ms, TE=52 ms
  - Resolution: 130×130x800 μm^3
  - Thickness = 0.8 mm
  - 16 averages

~10h



Ex-vivo mouse brain (37^{o}C)

- 9.4T Biospec
- DDE experiments:
  - Δ=12ms, t =12ms, δ=3ms
  - TR = 3000ms, TE=48.5 ms
  - Resolution: 200×200x1000 μm^3
  - 2 averages

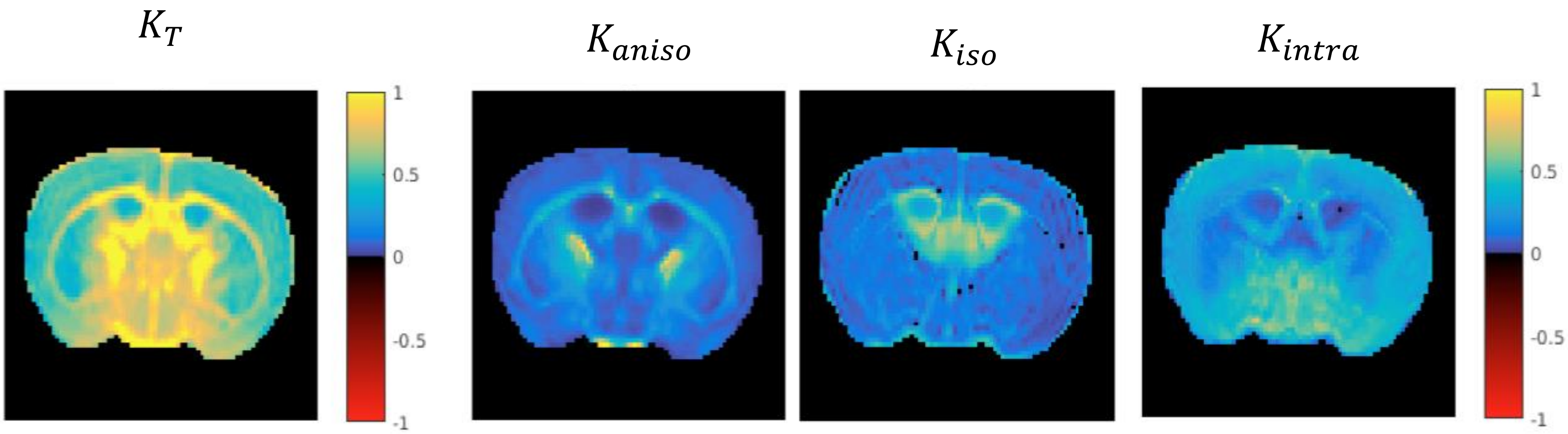
~2h

Two In-vivo rat brain

Correlation Tensor Imaging

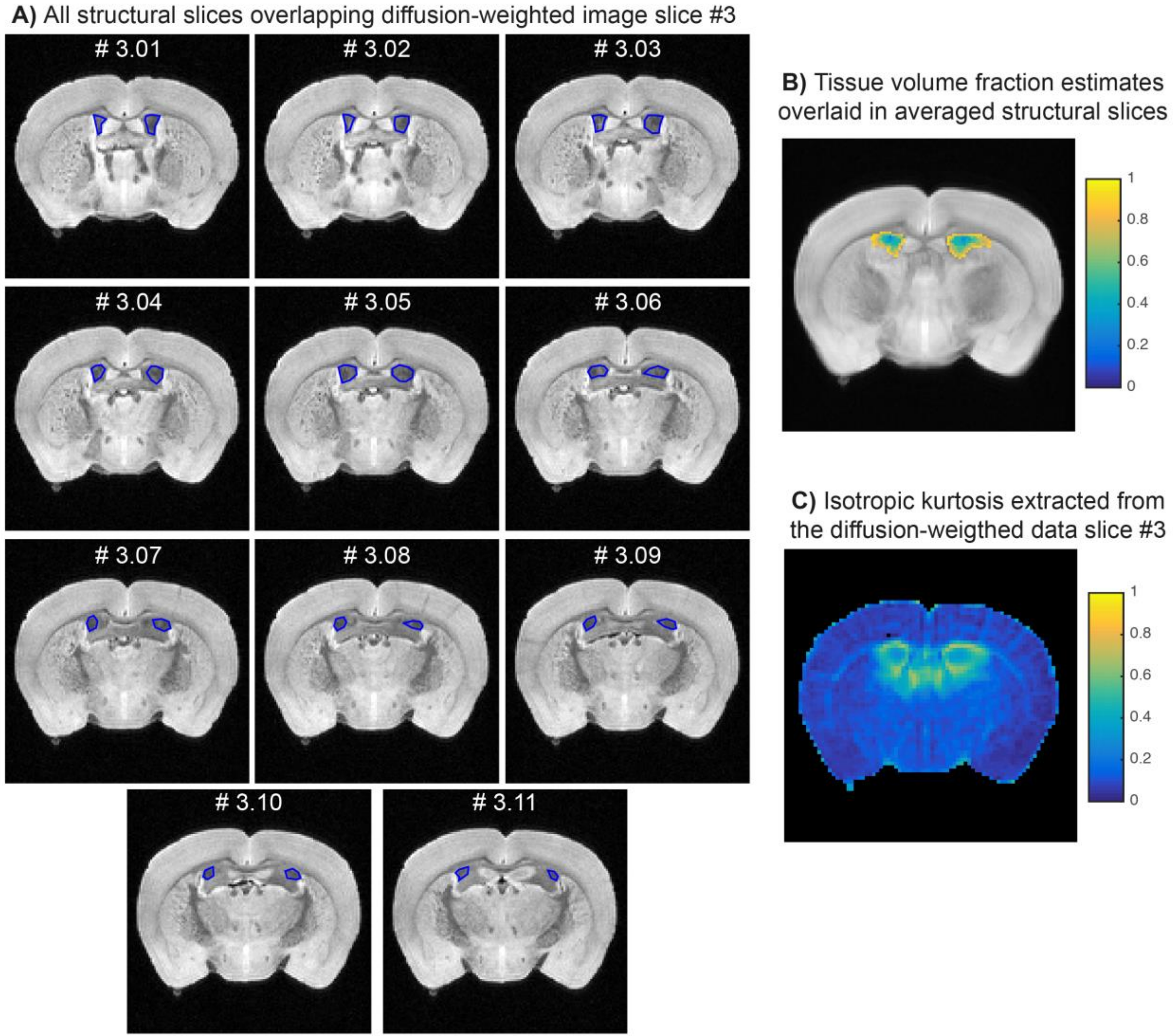
Ex-vivo results

Henriques et al. NeuroImage 2020



- K_{aniso} is the main source in white matter
- K_{iso} has larger values in the b
- K_{intra} is non zero

Measures do not depend on a microstructural model


A) All structural slices overlapping diffusion-weighted image slice #3
3.01
3.02
3.03
3.04
3.05
3.06
3.07
3.08
3.09
3.10
3.11
B) Tissue volume fraction estimates overlaid in averaged structural slices
1
0.8
0.6
0.4
0.2
0
C) Isotropic kurtosis extracted from the diffusion-weigthed data slice #3
1
0.8
0.6
0.4
0.2
0