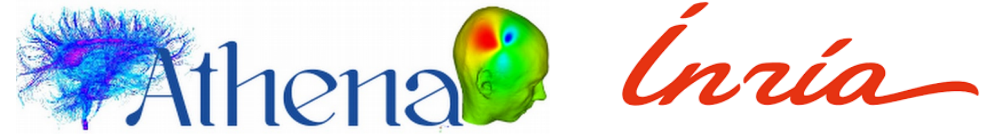


Inria Sophia Antipolis-Méditerranée
Université Côte d'Azur, FR
Athena Project-Team



UNIVERSITÉ CÔTE D'AZUR 

Spherical convolutional neural network for diffusion MRI analysis

Sara Sedlar

Abib Alimi

Théodore Papadopoulo

Rachid Deriche

Samuel Deslauriers-Gauthier



Overview

- Motivation to use spherical CNN
- Brain micro-structure modeling
- Theory behind
- Illustration of the architectures
- Experiments
- Conclusions & discussions

Signals on sphere

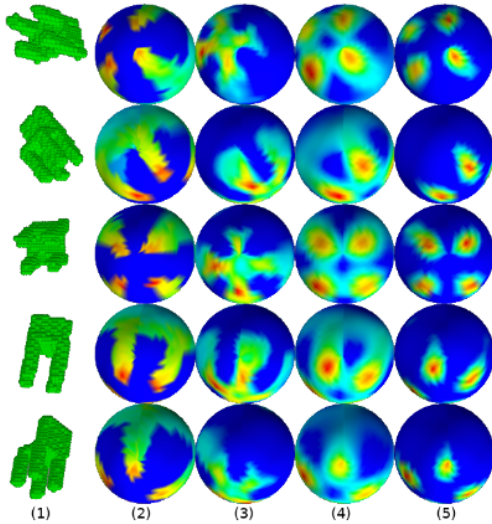


Figure 1. 3D object from ModelNet database and its projections on sphere [1]

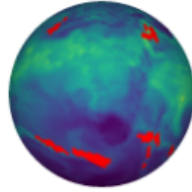


Figure 2. Segmentation of atmospheric rivers [2]



Figure 4. 360° image [4]

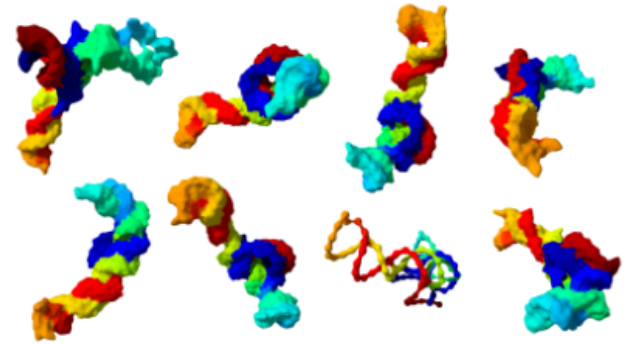


Figure 3. Segmentation of molecular surfaces [3]

[1] Esteves, Carlos, et al. "3D object classification and retrieval with Spherical CNNs." arXiv preprint arXiv:1711.06721 (2017).

[2] Jiang, Chiyu, et al. "Spherical cnns on unstructured grids." arXiv preprint arXiv:1901.02039 (2019).

[3] Poulénard, Adrien, et al. "Effective Rotation-invariant Point CNN with Spherical Harmonics kernels." 2019 International Conference on 3D Vision (3DV). IEEE, 2019.

[4] Coors, Benjamin, Alexandru Paul Condrache, and Andreas Geiger. "Spherenet: Learning spherical representations for detection and classification in omnidirectional images." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

Diffusion

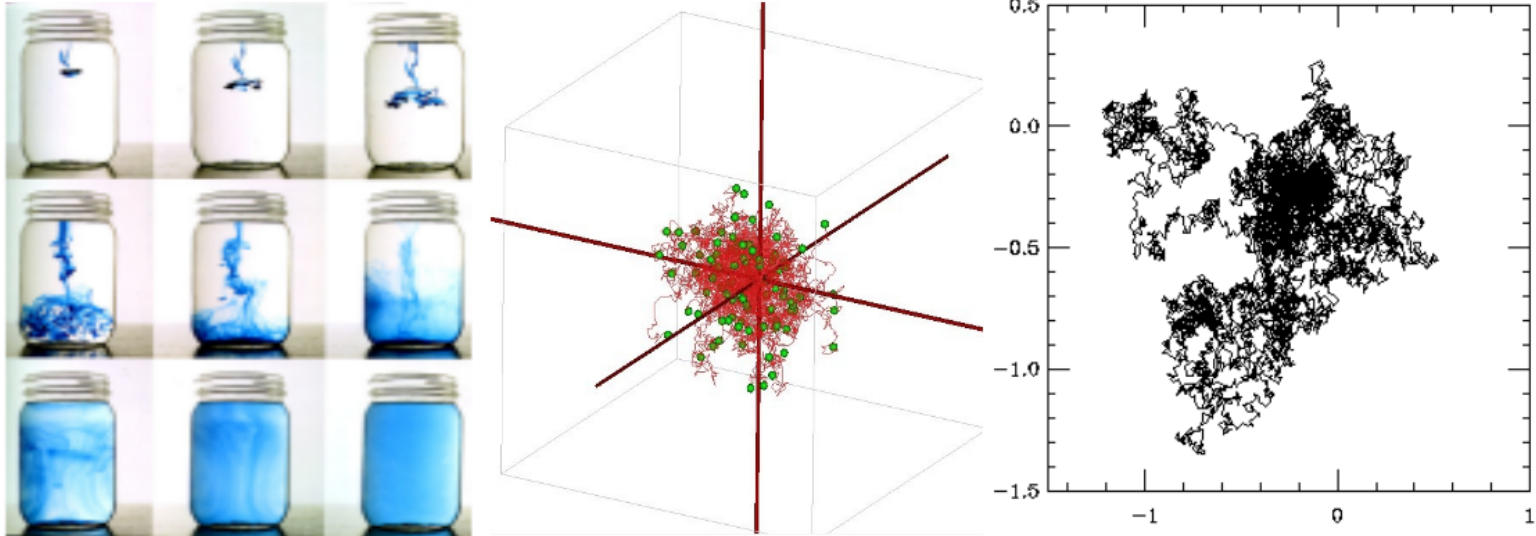


Figure 5. Illustration of diffusion in free and restricted volumes

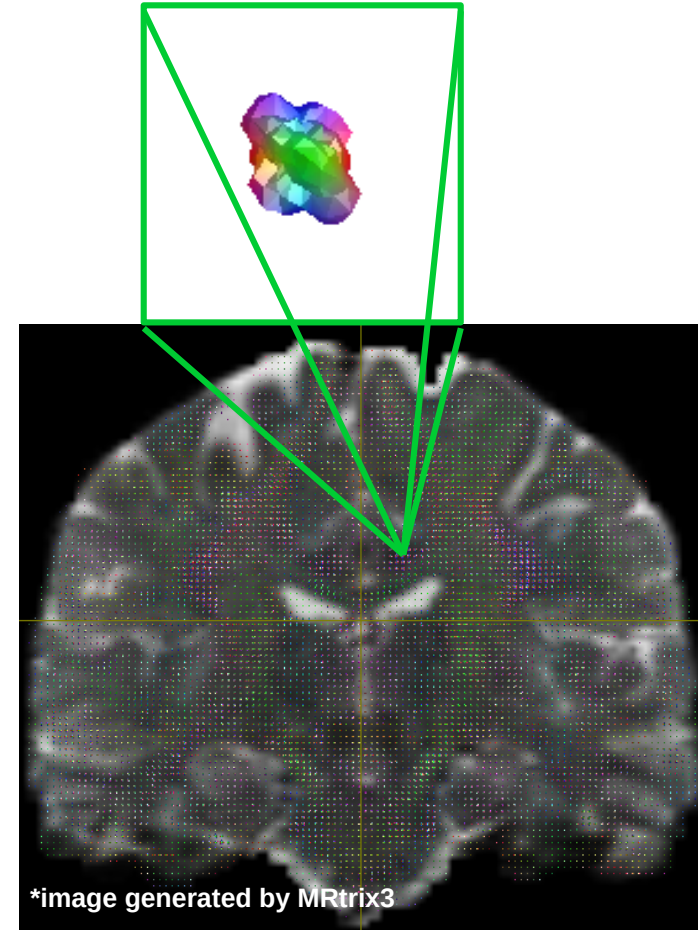
Image sources:

<https://hydrologie.org/glu/ZZ/GP0330.HTM> ,

https://web2.uwindsor.ca/courses/physics/high_schools/2005/Brownian_motion/2dbm.jpg

diffusion MRI (dMRI)

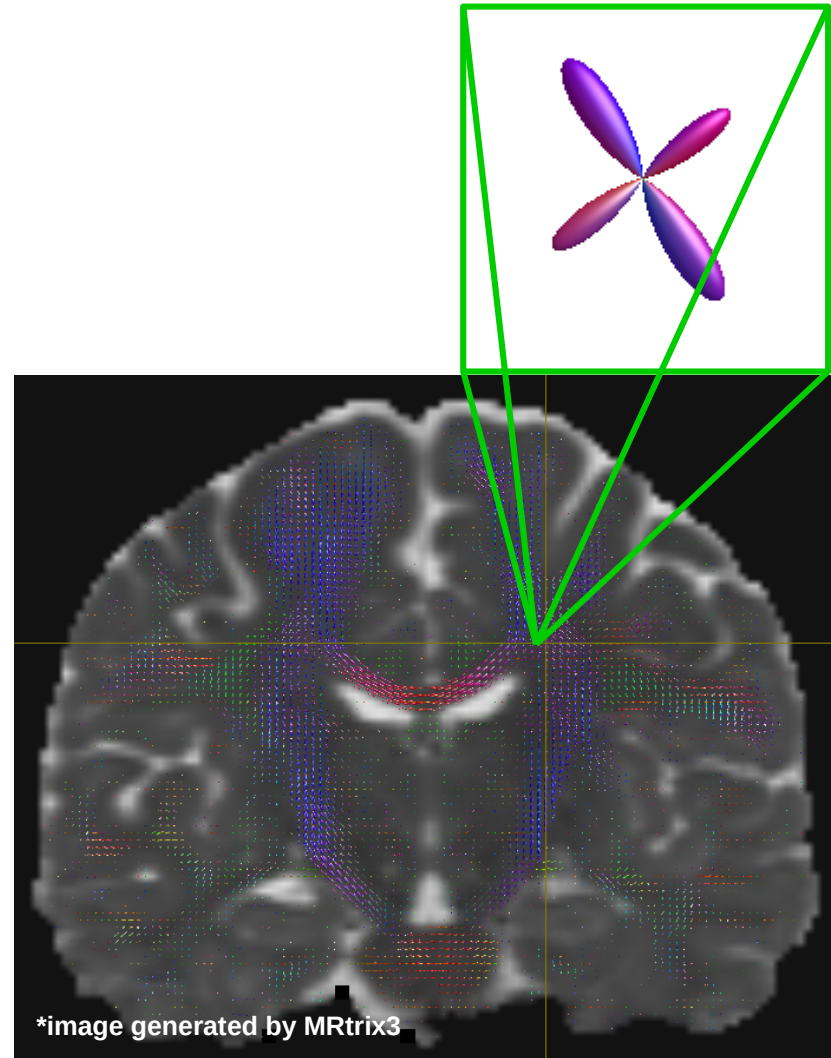
- Based on water molecule diffusion properties of underlying tissue
- Molecule motion in white matter (axons) is restricted
- Molecule motion in gray matter and cerebrospinal fluid is close to free
- Each voxel is a signal in 3D, often sampled on sphere
- Contains Rician noise
- **Crucial for white matter analysis!**



Brain micro-structure modeling

Fiber orientation distribution function (FOD)

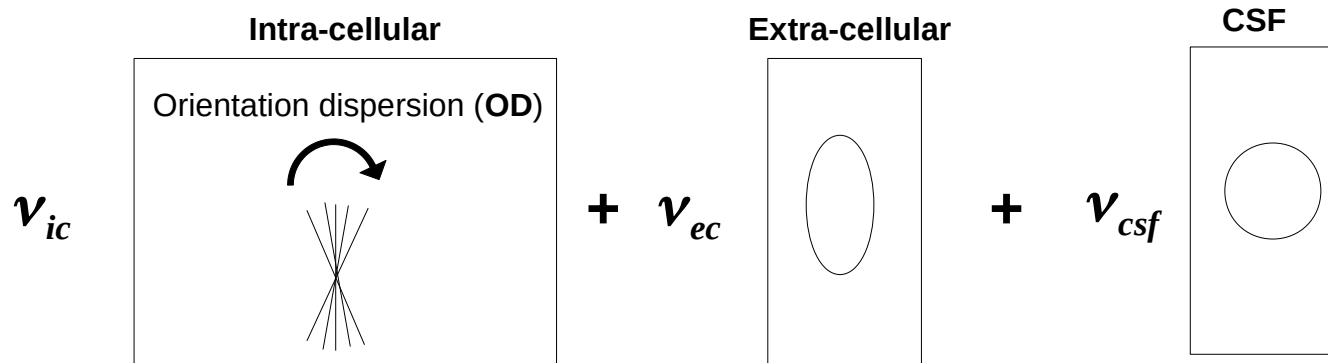
- Function on a sphere that reveals how the axon bundles are oriented in a voxel
- Important for tracking of white matter pathways



Brain micro-structure modeling

Neurite orientation dispersion and density imaging (NODDI) [5]

- A biophysical model that explains dMRI signal as a linear combination of three compartments
 - Intra-cellular – axons and dendrites
 - Extra-cellular – neuron cell bodies and glial cells
 - Cerebrospinal fluid (CSF)
- Showed potential in evaluation of several neurodegenerative diseases



Convolution on a sphere

Planar correlation (convolution) of two \mathbb{R}^2 signals is a signal in \mathbb{R}^2

Spherical correlation (convolution) of two S^2 signals is a signal in $SO(3)$

Space of **translational** moves in plane (\mathbb{R}^2) is in \mathbb{R}^2 (isomorphic to plane)

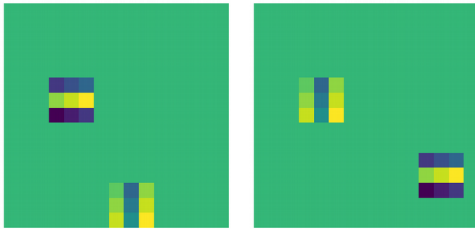


Figure 6. Translational movements of patterns in plane

Space of **3D rotational** moves on sphere (S^2) is $SO(3)$ manifold.

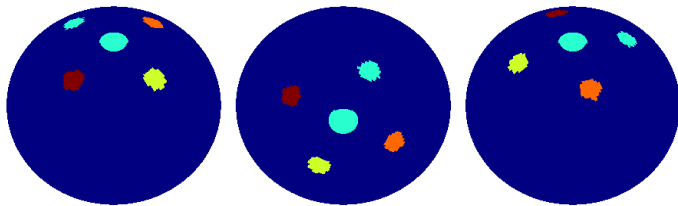


Figure 7. Rotational movements of patterns on sphere

3D rotational group or $SO(3)$ manifold: group of all rotations around origin in 3D Euclidean space

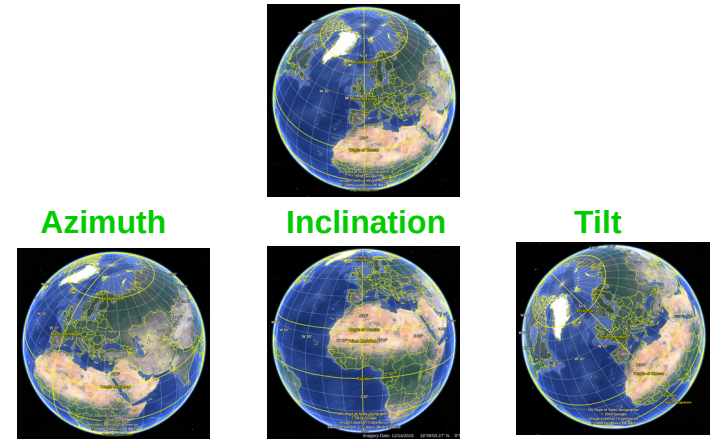


Figure 8. 3D rotation
(images generated by Google Earth)

Convolution on a sphere

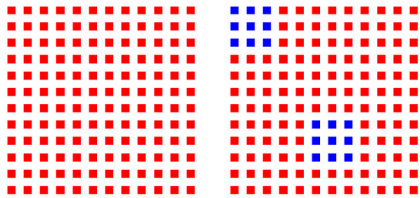


Figure 9. Kernel movement in plane

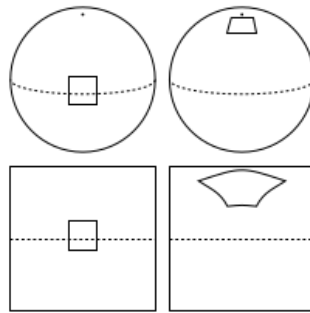


Figure 10. Illustration of deformation introduced by projection of spherical signal on plane
(**image source:** Spherical CNNs, Taco S. Cohen et al.)

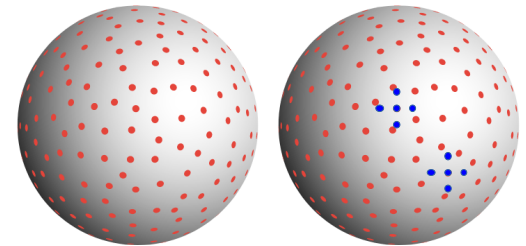
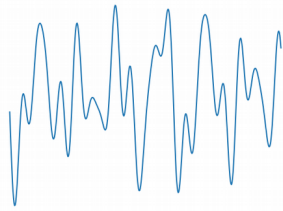
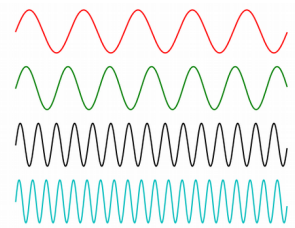


Figure 11. Kernel movement in $SO(3)$
(image generated using **Q-ball sampling tool**)

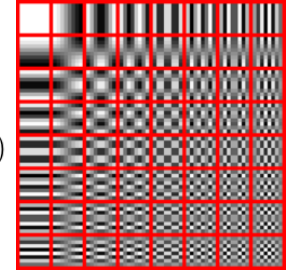
Fourier transform



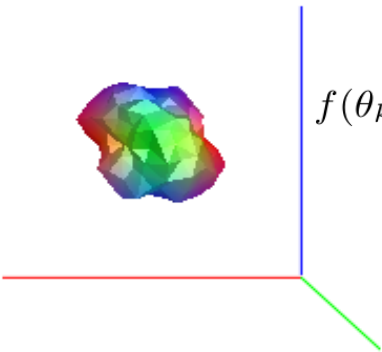
$$f(n) = \frac{1}{N} \sum_{k=0}^{N-1} F(k) \cdot e^{i2\pi kn/N}$$



$$f(n, m) = \frac{1}{NM} \sum_{u=0}^{N-1} \sum_{v=0}^{M-1} F(u, v) \cdot e^{i2\pi(\frac{un}{N} + \frac{vm}{M})}$$



Spherical signals can be represented as a linear combination of spherical harmonics:



$$f(\theta_k, \phi_k) = \sum_{l=0}^L \sum_{m=-l}^{m=l} \hat{f}_l^m Y_l^m(\theta_k, \phi_k)$$

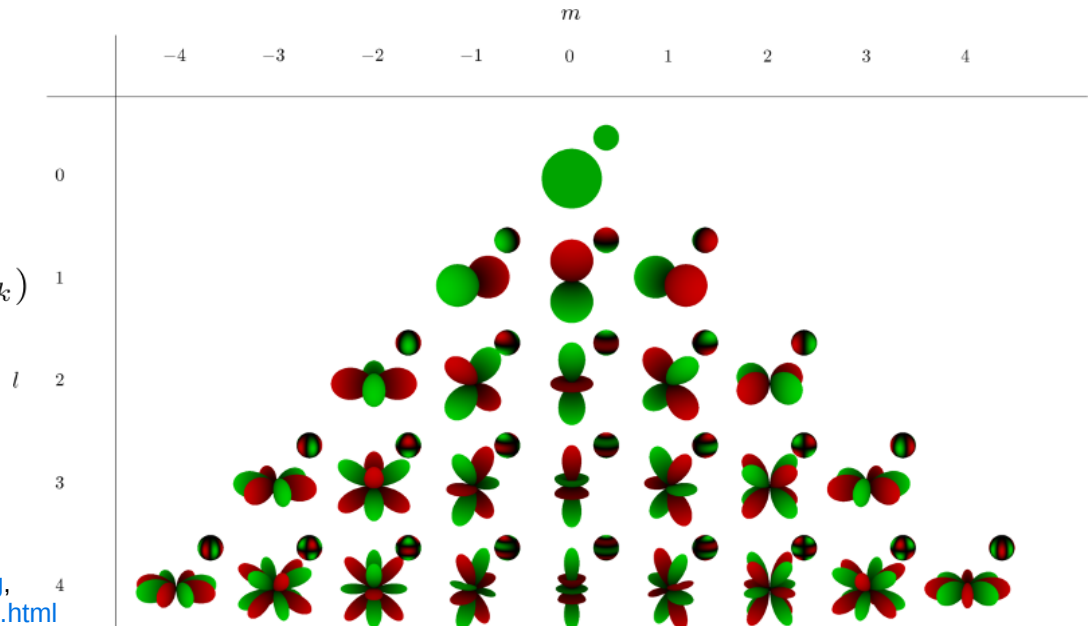


Image sources:

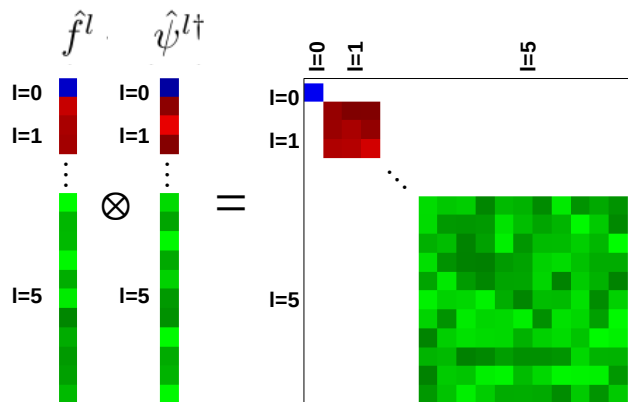
- https://en.wikipedia.org/wiki/Multidimensional_transform#/media/File:Dctjpeg.png
- <https://www.ti.uni-bielefeld.de/html/people/ddiffert/libShc/manual/fouriertransform.html>

Spherical CNNs [6]

S² signals

$$[\psi \star f](R) = \langle L_R \psi, f \rangle = \int_{S^2} \sum_{k=1}^K \psi_k(R^{-1}x) f_k(x) dx.$$

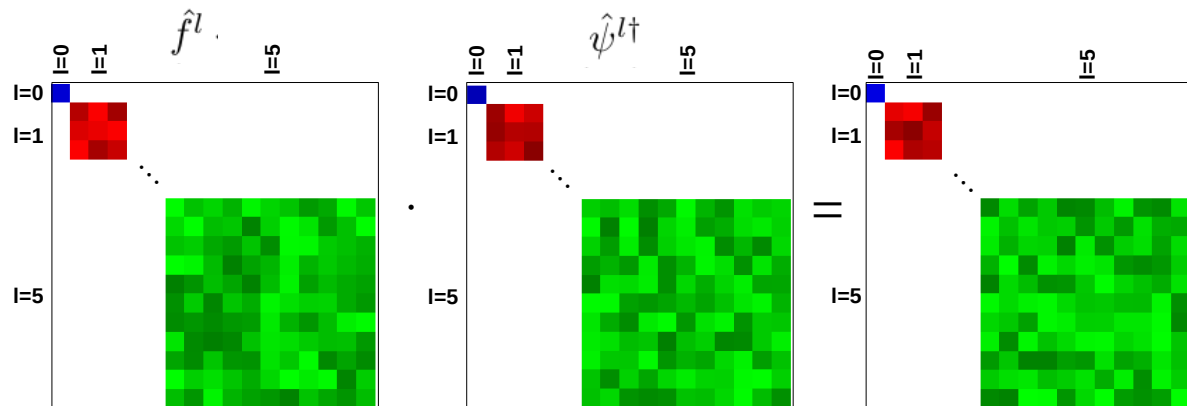
$$\widehat{\psi \star f}^l = \hat{f}^l \cdot \hat{\psi}^{l\dagger}$$



SO(3) signals

$$[\psi \star f](R) = \langle L_R \psi, f \rangle = \int_{\text{SO}(3)} \sum_{k=1}^K \psi_k(R^{-1}Q) f_k(Q) dQ.$$

$$\widehat{\psi \star f}^l = \hat{f}^l \cdot \hat{\psi}^{l\dagger}$$

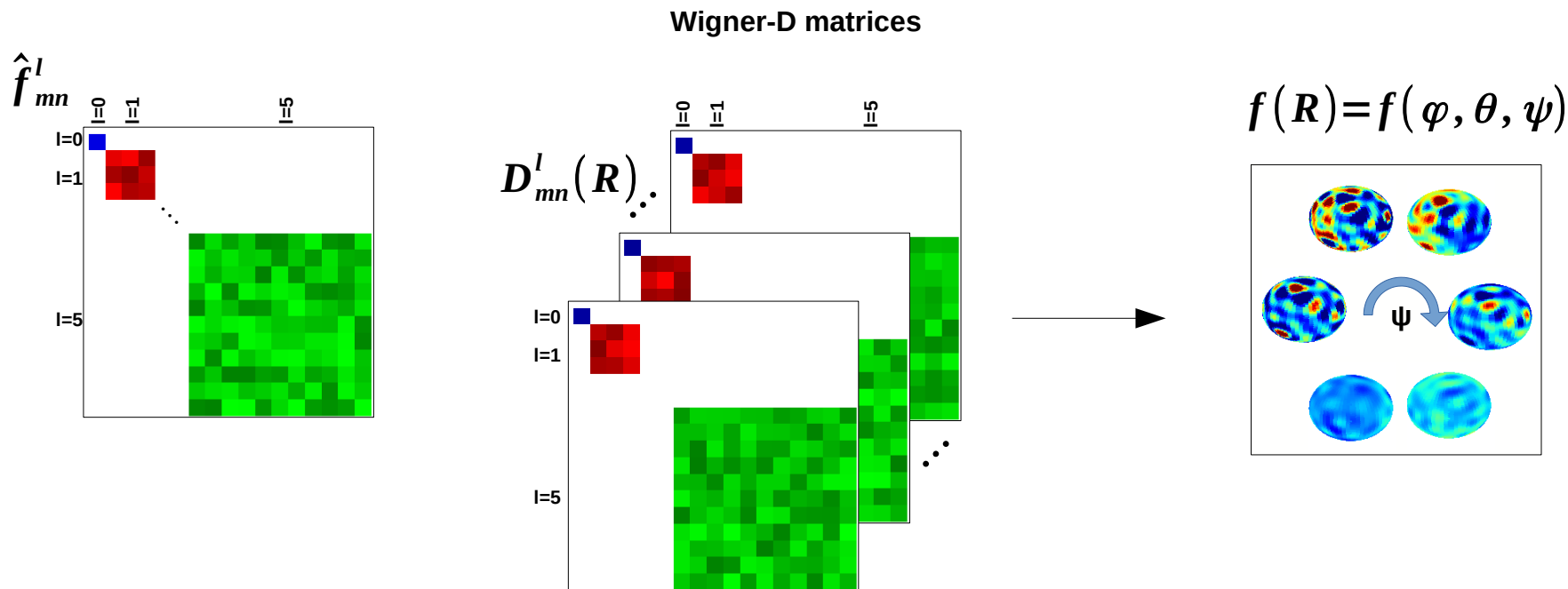


Spherical CNNs [6]

Transformation from Fourier domain to $SO(3)$ is given by:

$$f(R) = \sum_{l=0}^b (2l+1) \sum_{m=-l}^l \sum_{n=-l}^l \hat{f}_{mn}^l D_{mn}^l(R),$$

where $D_{mn}^l(R)$ are Wigner D matrices



Adjustments to dMRI data properties

Antipodally symmetric → basis of even order are sufficient for their representation

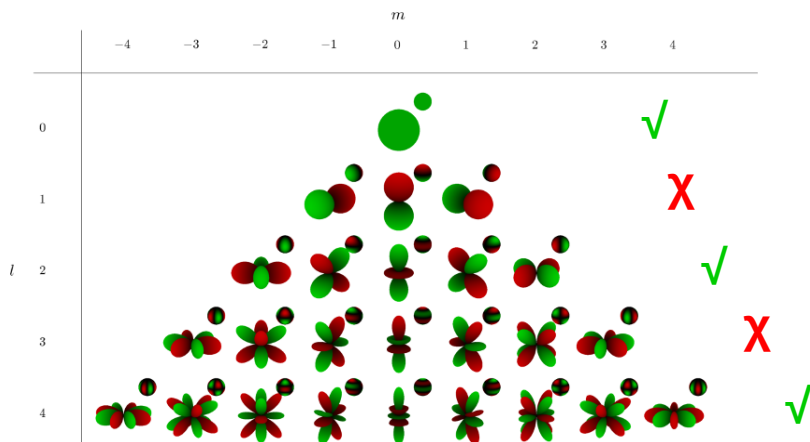


Figure 12. Illustration of spherical harmonics

Real signal → real basis are sufficient for their representation

Real spherical harmonics

$$Y_{lm} = \begin{cases} \sqrt{2}(-1)^m \Im(Y_l^{|m|}), & \text{if } m < 0 \\ Y_l^m, & \text{if } m = 0 \\ \sqrt{2}(-1)^m \Re(Y_l^m), & \text{if } m > 0 \end{cases}$$

Real Wigner D matrices

$$D_{lmn} = \begin{cases} (-1)^{m+n} \Re(D_l^{mn}) + (-1)^m \Re(D_l^{m-n}), & \text{for } m > 0, n > 0 \\ -(-1)^{m+n} \Im(D_l^{|m||n|}) + (-1)^m \Im(D_l^{mn}), & \text{for } m > 0, n < 0 \\ (-1)^{m+n} \Im(D_l^{|m|n}) + (-1)^m \Im(D_l^{|m|-n}), & \text{for } m < 0, n > 0 \\ (-1)^{m+n} \Re(D_l^{|m||n|}) - (-1)^m \Re(D_l^{|m|n}), & \text{for } m < 0, n < 0 \end{cases}$$

$$D_{l0n} = \begin{cases} \sqrt{2}(-1)^n \Im(D_l^{0|n|}), & \text{if } n < 0 \\ D_l^{0n}, & \text{if } n = 0 \\ \sqrt{2}(-1)^n \Re(D_l^{0n}), & \text{if } n > 0 \end{cases} \quad D_{lm0} = \begin{cases} \sqrt{2}(-1)^m \Im(D_l^{|m|0}), & \text{if } m < 0 \\ D_l^{m0}, & \text{if } m = 0 \\ \sqrt{2}(-1)^m \Re(D_l^{m0}), & \text{if } m > 0 \end{cases}$$

Orthogonality loss

Continuous signals

Fourier Transform (FT)

$$\hat{f}(\xi) = \int_{-\infty}^{\infty} f(t) e^{-i2\pi\xi t} dt$$

$$\hat{f}_l^m = \int_{\Omega} f(\theta, \phi) Y_l^{m*}(\theta, \phi) d\Omega$$

inverse Fourier Transform (IFT)

$$f(t) = \int_{-\infty}^{\infty} f(\xi) e^{i2\pi t\xi} d\xi$$

$$f(\theta, \phi) = \sum_{l=0}^{\infty} \sum_{m=-l}^{m=l} \hat{f}_l^m Y_l^m(\theta, \phi)$$

Discrete signals

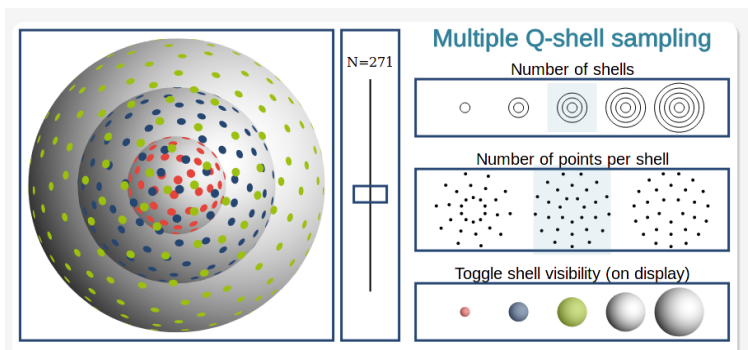
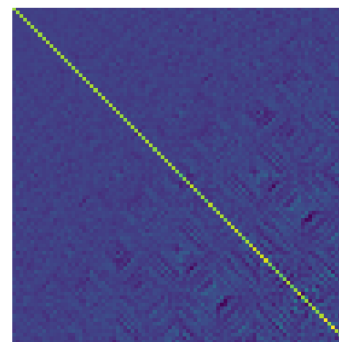


Figure 13. Illustration of gradient direction sampling scheme [7] (image source: <http://www.emmanuelcaruyer.com/q-space-sampling.php>)

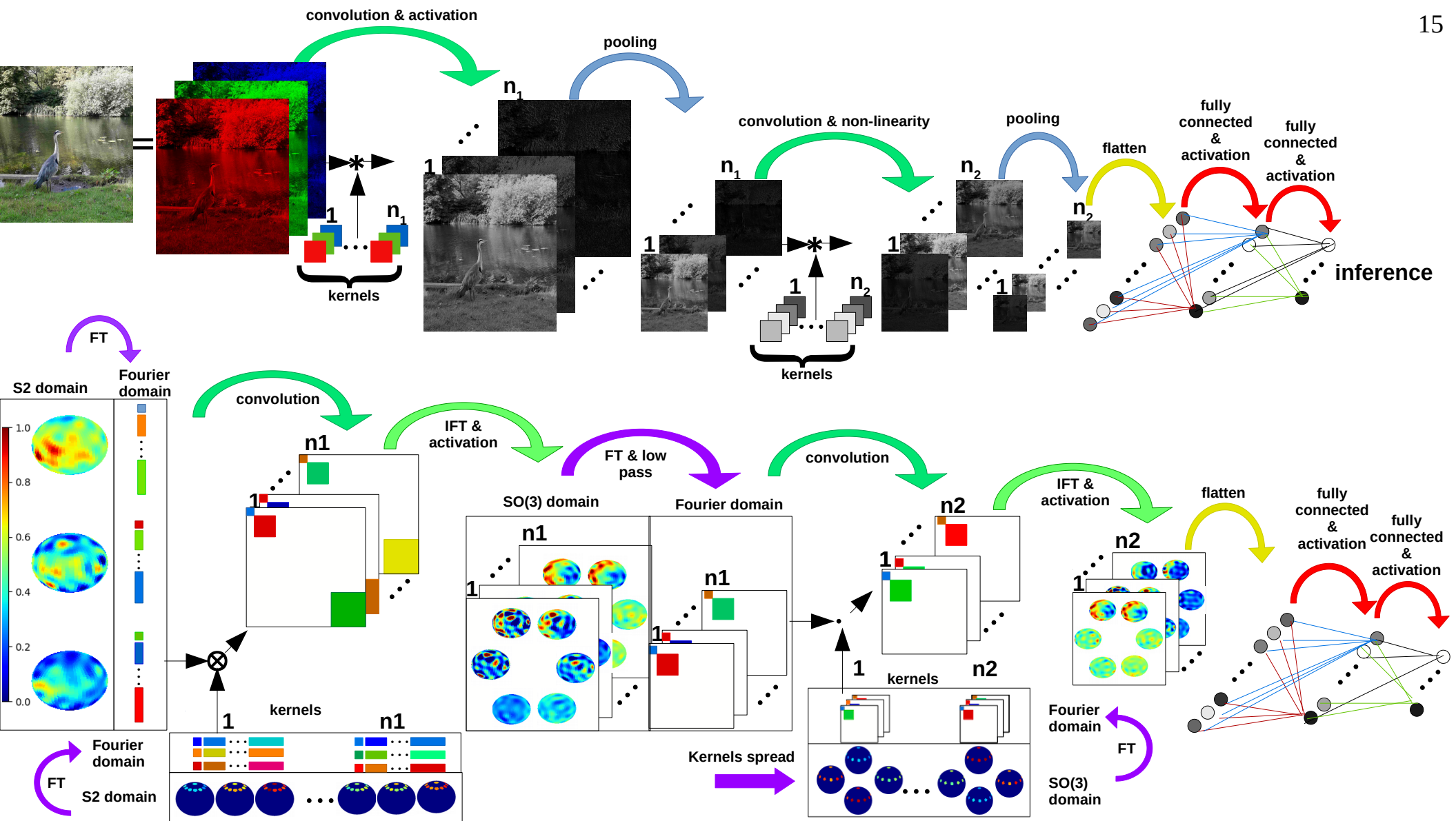
$$Y_l^m(\theta_k, \phi_k) Y_l^m(\theta_k, \phi_k)^*$$



$$Y_l^m(\theta_k, \phi_k) Y_l^m(\theta_k, \phi_k)^\dagger$$

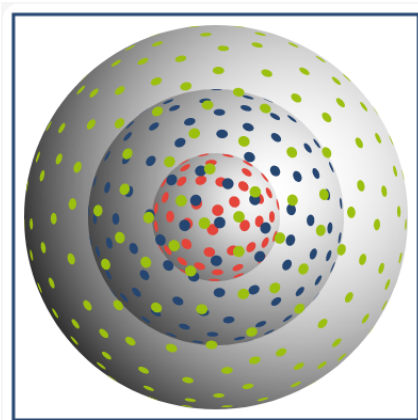


Figure 14. Loss of orthogonality of transposed and pseudo inverted basis



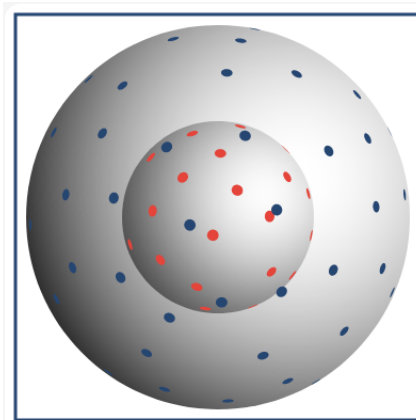
NODDI parameter estimation – experiment

Golden standard generated
by AMICO [8]
with full sampling scheme



Full sampling scheme

Experiments run on
downsampled scheme



Downsampled sampling scheme

Spherical CNN model parameters:

- 4 convolutional + 4 fully connected layers
- Total number of trainable parameters: 103 891

Model trained on HCP [9] dataset:

- 30 subjects for training
- 10 subjects for validation
- 10 subjects for test

Model trained to estimate three NODDI parameters: ν_{ic} ν_{csf} **OD**

[8] Daducci, Alessandro, et al. "Accelerated microstructure imaging via convex optimization (AMICO) from diffusion MRI data." *Neuroimage* 105 (2015): 32-44.

[9] Van Essen, David C., et al. "The WU-Minn human connectome project: an overview." *Neuroimage* 80 (2013): 62-79.

image source: <http://www.emmanuelcaruyer.com/q-space-sampling.php>

NODDI parameter estimation – results

Method is compared with another deep learning approach MEDN [10]

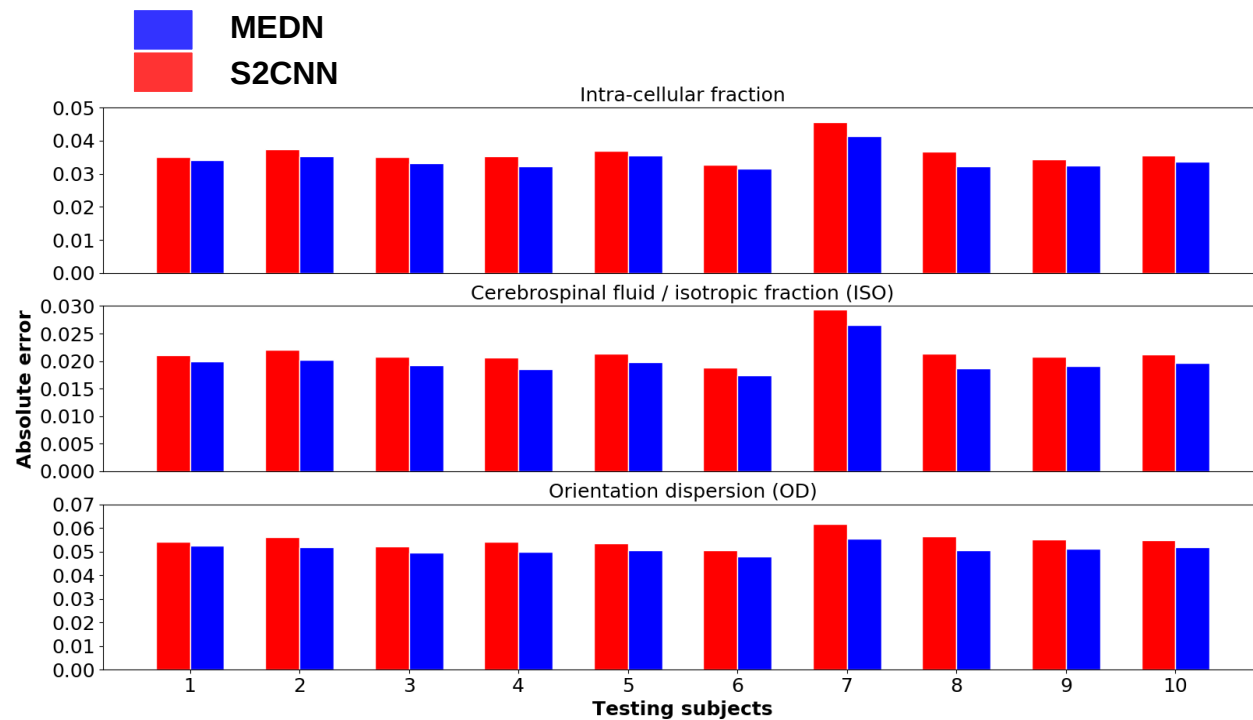
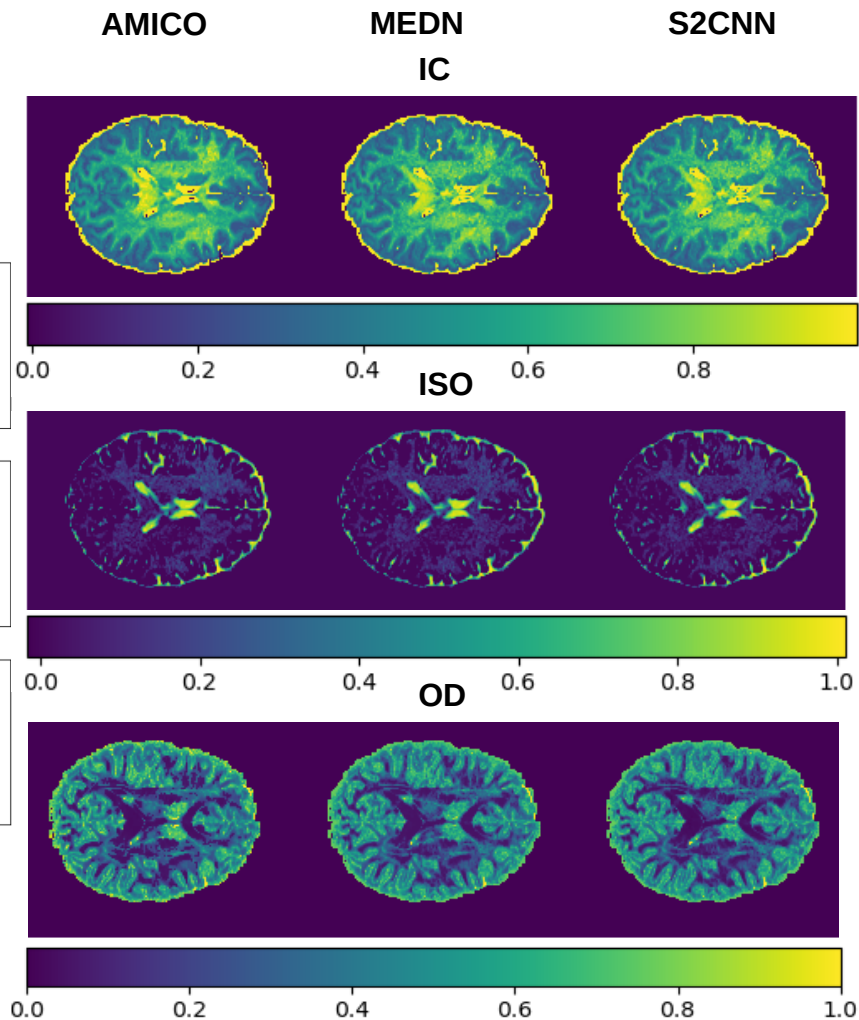


Figure 16. NODDI estimation errors from for S2CNN and MEDN



FOD estimation – experiment

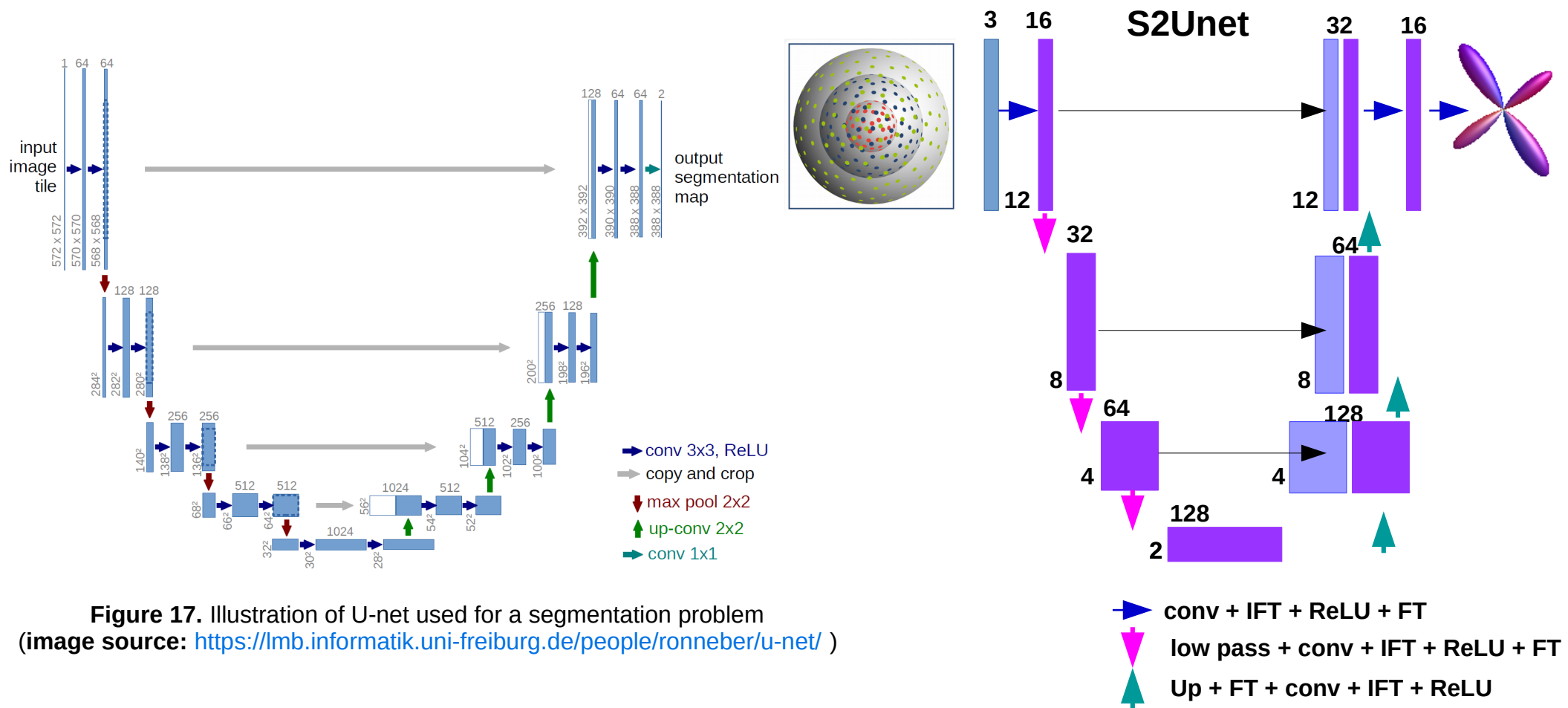
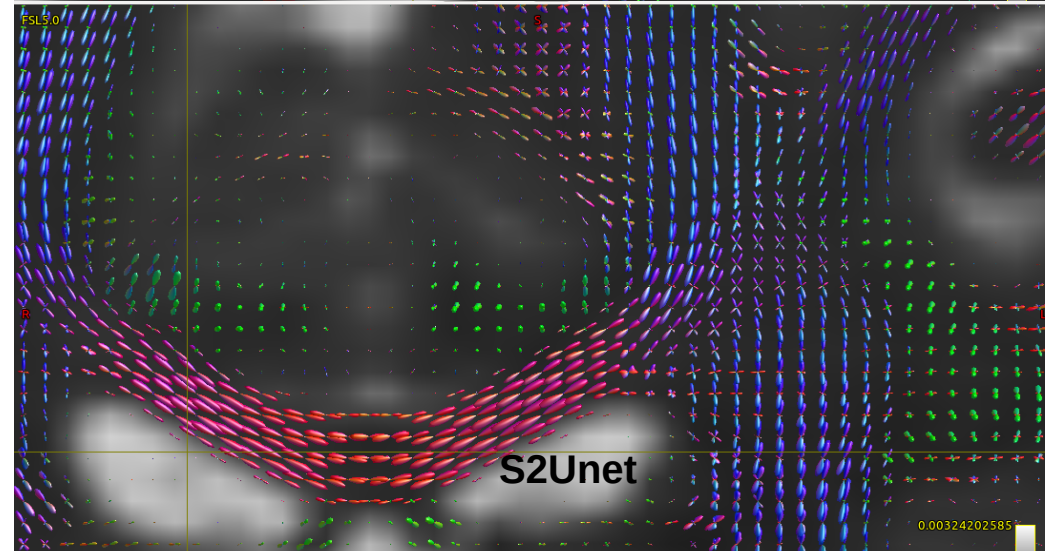
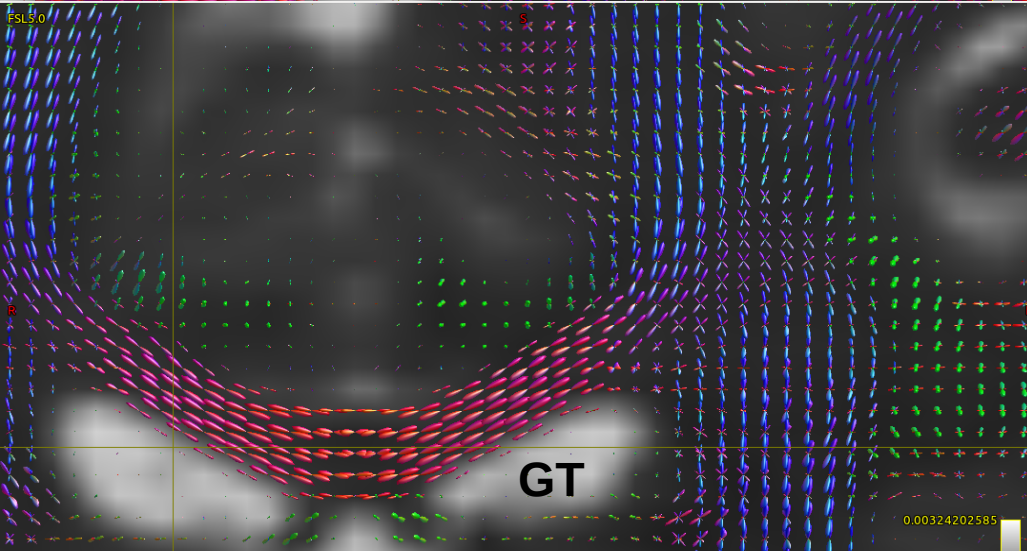
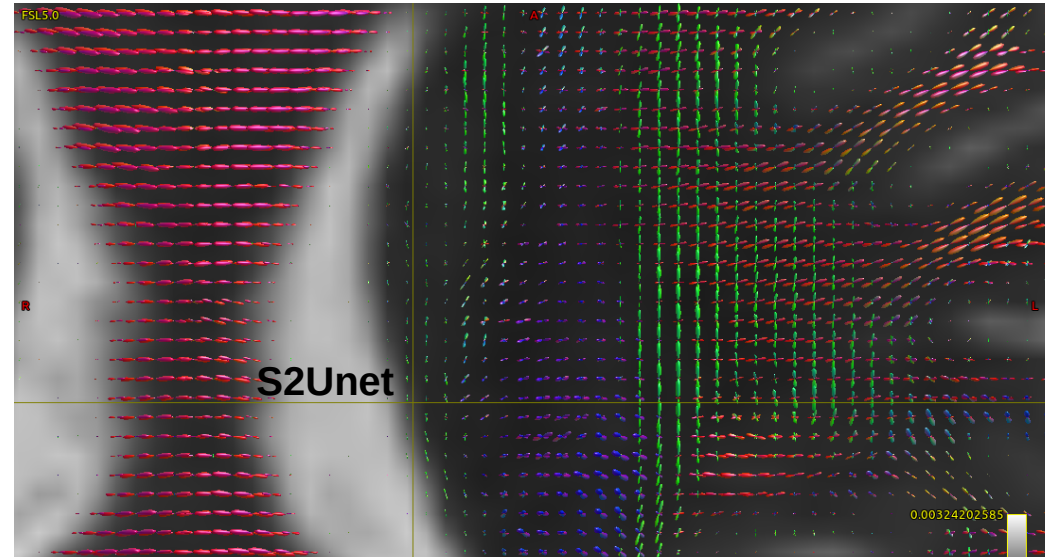
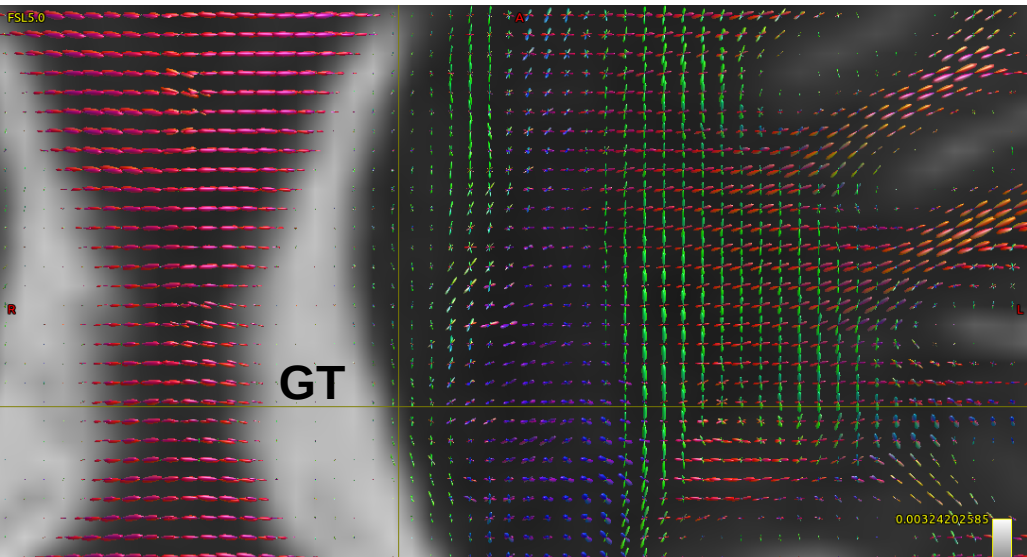


Figure 17. Illustration of U-net used for a segmentation problem (image source: <https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/>)



[12] Jeurissen, Ben, et al. "Multi-tissue constrained spherical deconvolution for improved analysis of multi-shell diffusion MRI data." *NeuroImage* 103 (2014): 411-426

Conclusions & discussions

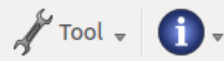
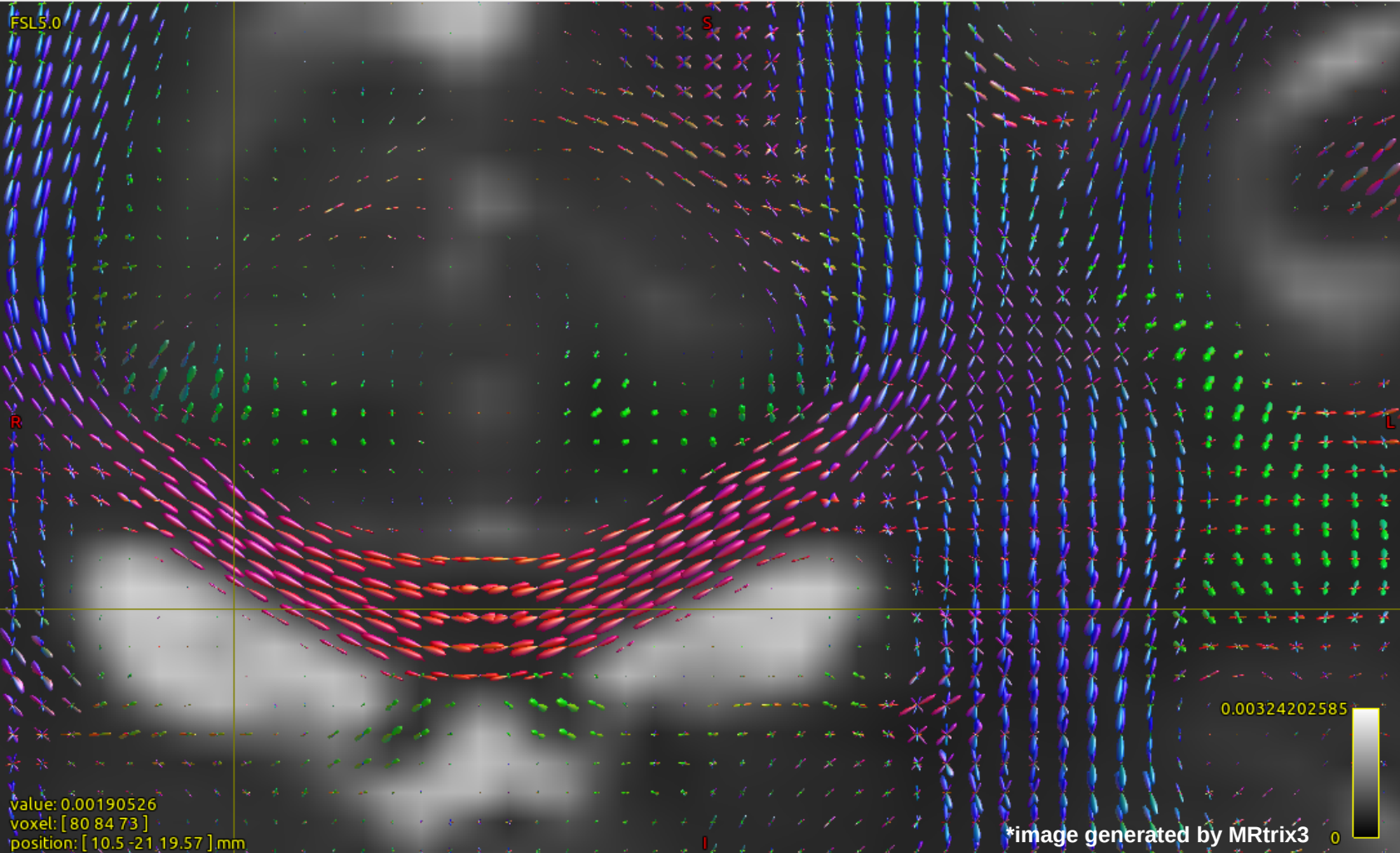
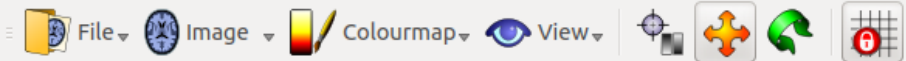
- We have investigated and shown how to use and adjust S2CNNs to dMRI data
- Promising results were obtained for two challenging tasks
- How to use synthetic data with known ground truth
- How to use another properties, such as axial symmetry of the signals generated by individual axon bundles
- How to avoid computationally expensive conversions to and from Fourier domain
- ...

Thank you for your attention! Questions?

Acknowledgement:

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This work has been partly supported by the French government, through the 3IA Côte d'Azur Investments in the Future project managed by the National Research Agency (ANR) with the reference number ANR-19-P3IA-0002.



ODF display



fod_wm.mif
 ...final/test/162733/unet_estim.mif

Golden standard

Inspect ODF at focus

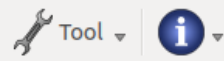
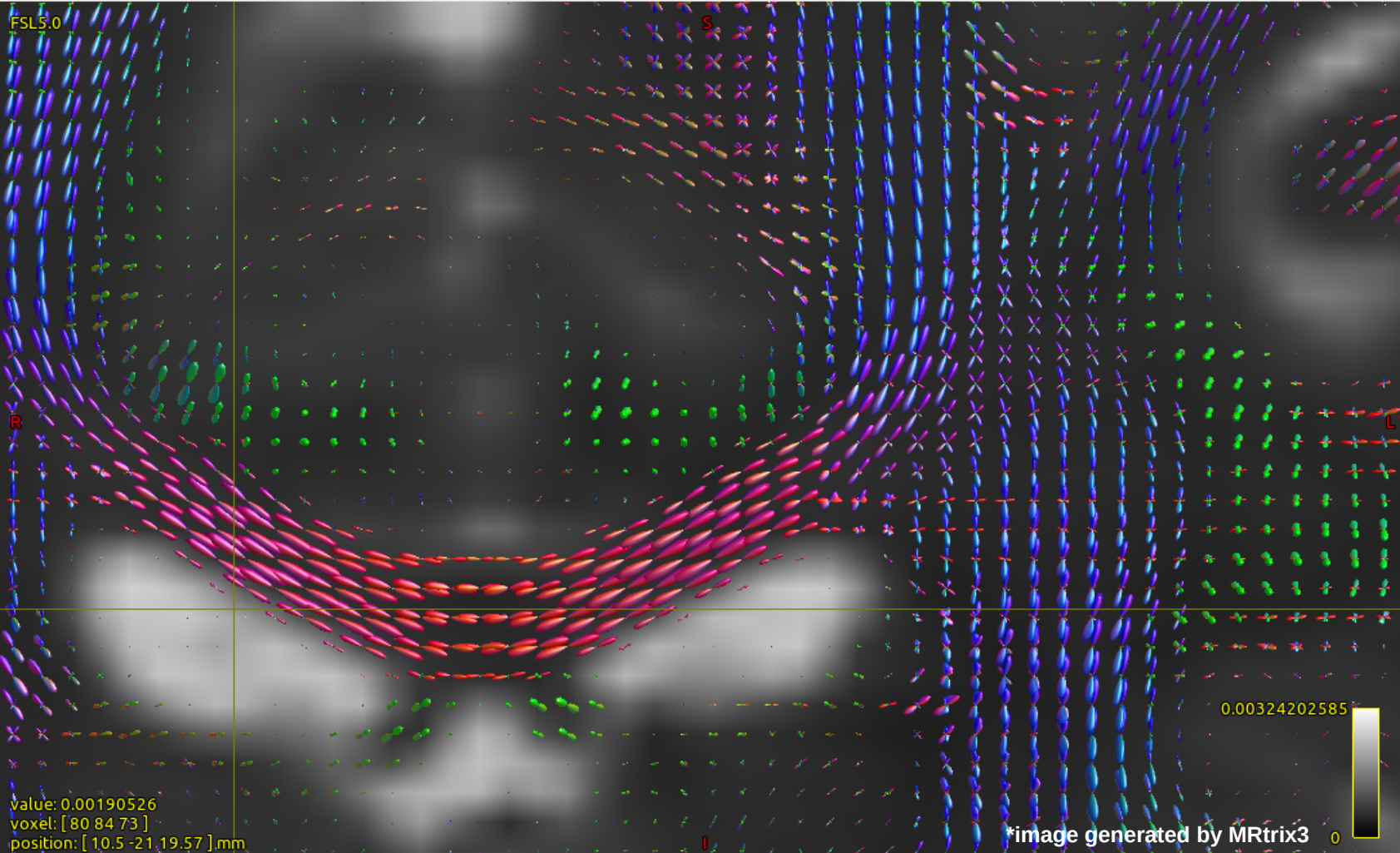
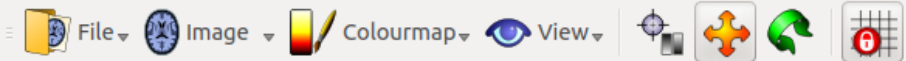
Display settings

detail 3 lmax 12

scale 1

- interpolation
- hide negative values
- lock to grid
- colour by direction
- use main grid
- use lighting

ODF lighting...



ODF display



fod_wm.mif
 ...final/test/162733/unet_estim.mif

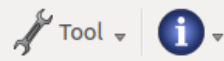
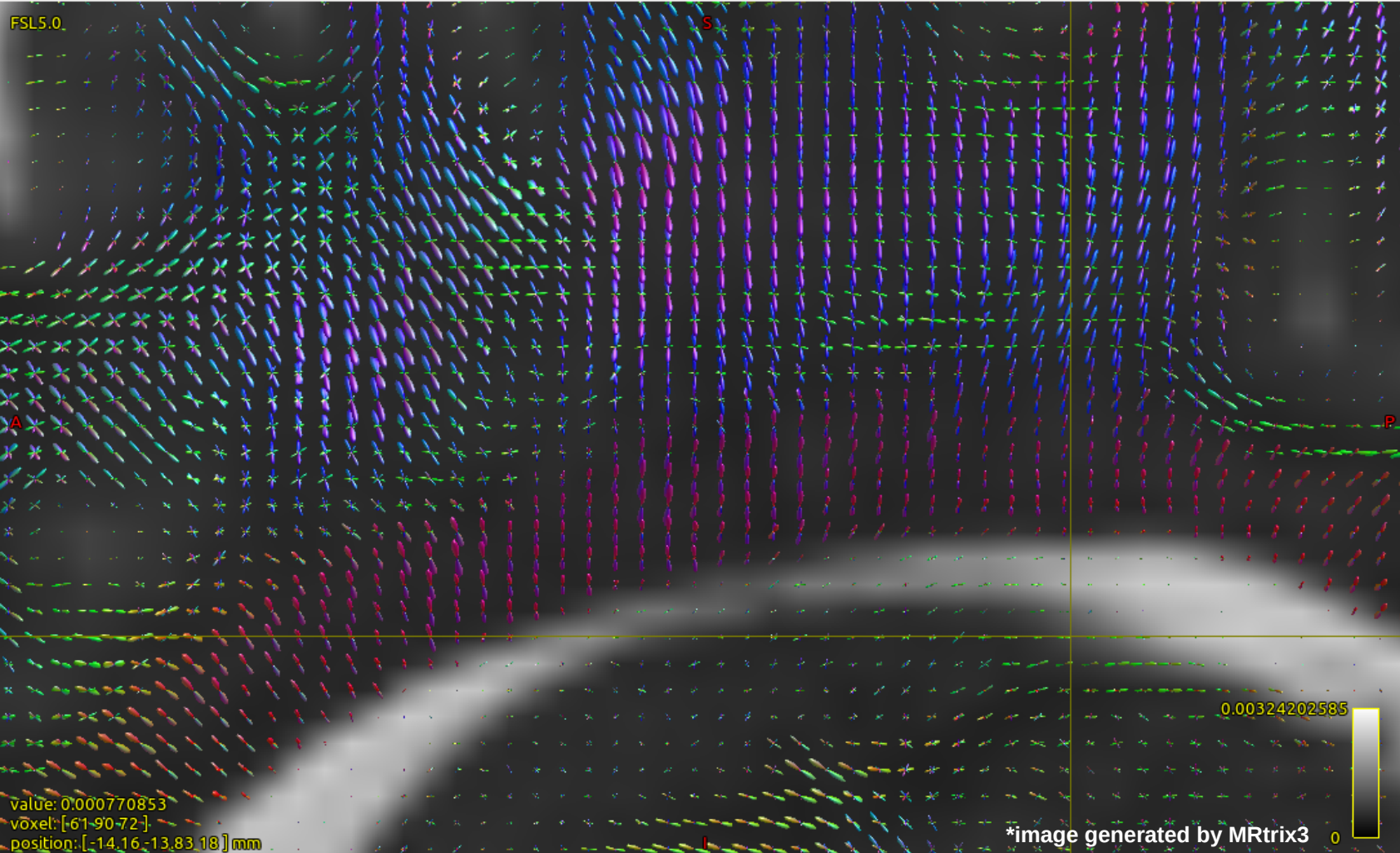
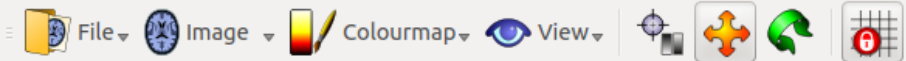
S2Unet

Inspect ODF at focus

Display settings

- detail lmax
- scale
- interpolation hide negative values
- lock to grid colour by direction
- use main grid use lighting

ODF lighting...



ODF display



fod_wm.mif
 ...final/test/162733/unet_estim.mif

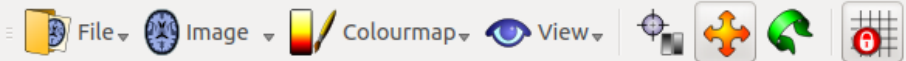
Golden standard

Inspect ODF at focus

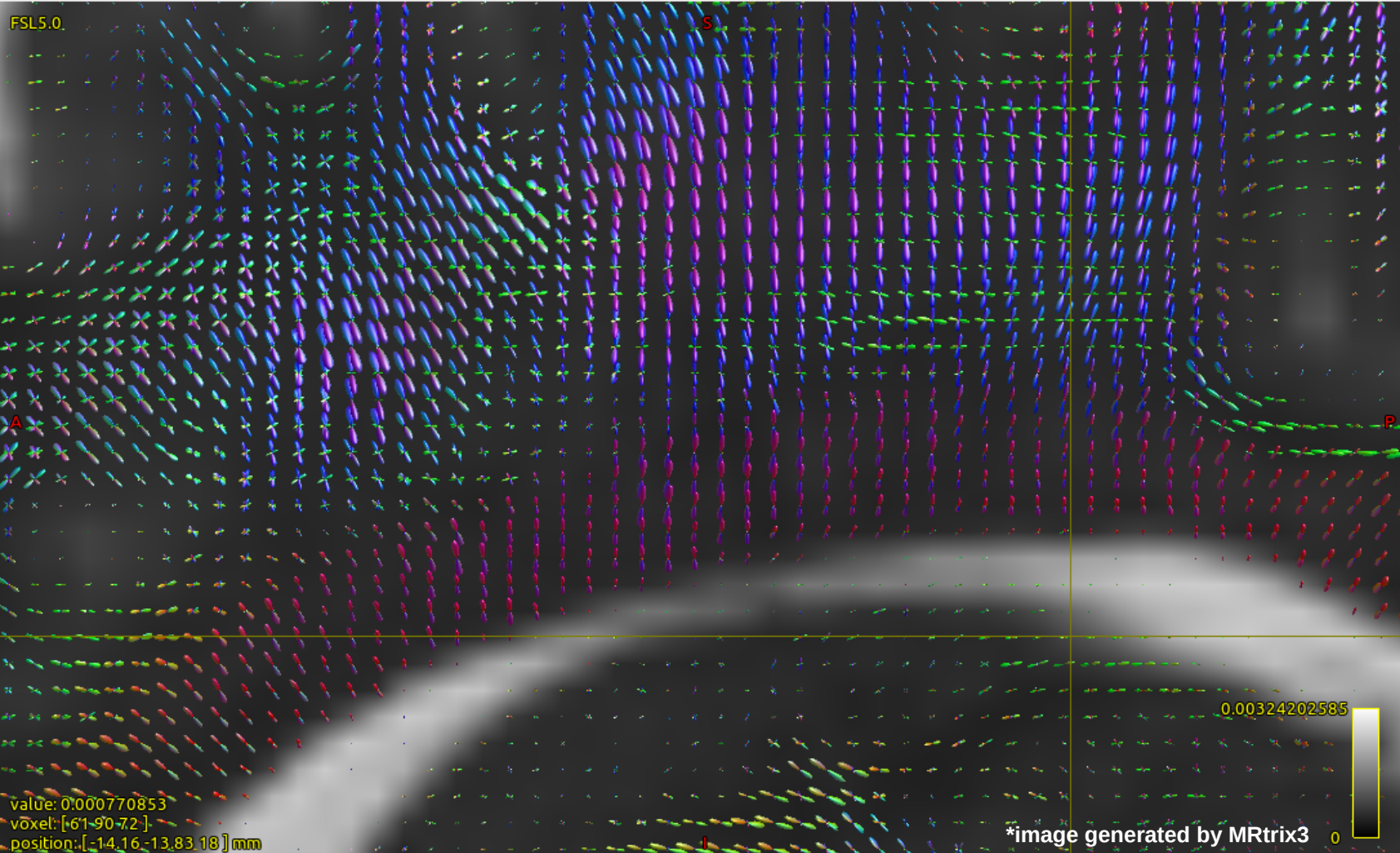
Display settings

- detail lmax
- scale
- interpolation hide negative values
- lock to grid colour by direction
- use main grid use lighting

ODF lighting...



FSL5.0



ODF display



fod_wm.mif
 ...final/test/162733/unet_estim.mif

S2Unet

Inspect ODF at focus

Display settings

detail lmax

scale

- interpolation
- hide negative values
- lock to grid
- colour by direction
- use main grid
- use lighting

ODF lighting...

value: 0.000770853
 voxel: [61 90 72]
 position: [-14.16 -13.83 18] mm

0.00324202585

*image generated by MRtrix3