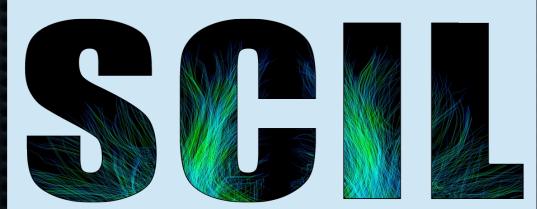
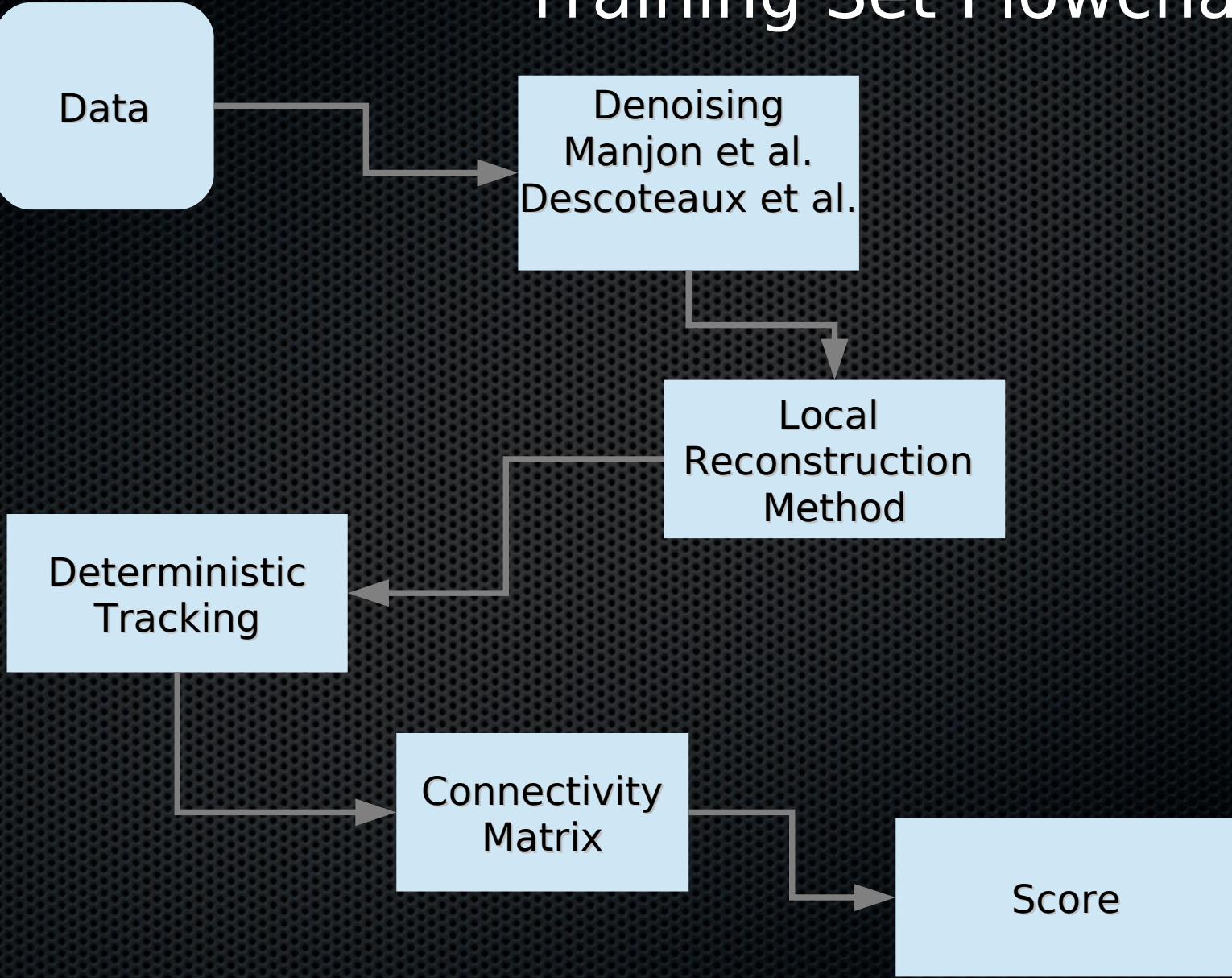


# Evaluating 5 reconstruction methods in all three categories

Eleftherios Garyfallidis and Michael Paquette  
Université de Sherbrooke, Quebec, Canada  
[scil.dinf.usherbrooke.ca](http://scil.dinf.usherbrooke.ca)



# Training Set Flowchart



# Local Reconstruction Methods

DTI/HARDI

**CSD**: Constrained Spherical Deconvolution

Tournier et al.

**SDT**: Spherical Deconvolution Transform

Descoteaux et al.

**PSO**: Multi-tensor with particle swarming.

Paquette et al.

**DSID**: Diffusion Spectrum Imaging with Deconvolution

Canales-Rodriguez et al.

**GQID**: Generalized Q-sampling Imaging with Spherical  
Deconvolution

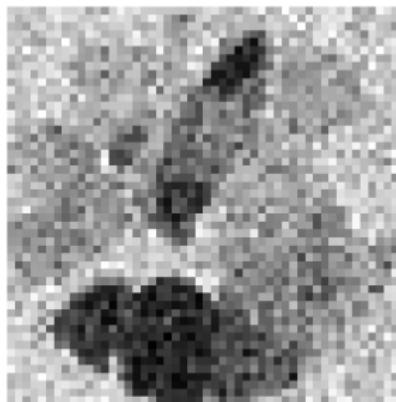
Garyfallidis PhD thesis

Heavyweight

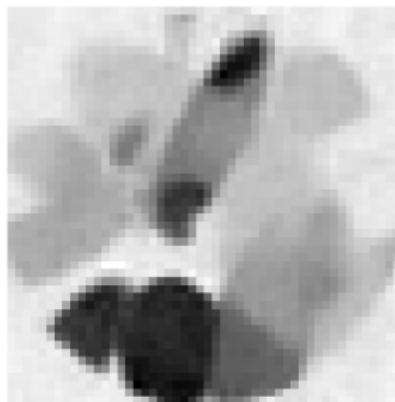
# Denoising

Adaptive non-local means denoising method

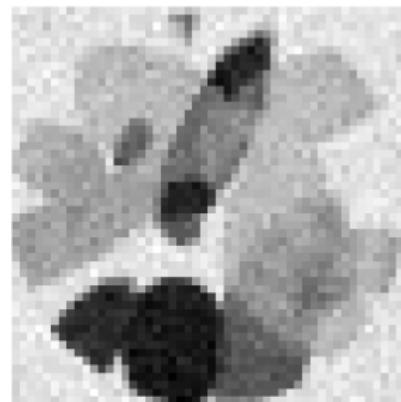
SNR = 10



SNR = 10 Denoised



SNR = 30



[Manjón, Coupé et al., 2010]

# Multi-Tensor Model

The Multi-Tensor (MT) generative model:

$$S(b, g) = \sum_{i=0}^{N-1} f_i e^{-bg^t D_i g}$$

where

$b$ ,  $g$  are the gradient b-value and unit orientation,  
 $f_i$  is the volume fraction of the  $i^{th}$  compartment,  
 $D_i$  is the symmetric rank-2 tensor of the  $i^{th}$  compartment,  
 $N$  is the number of compartment,

$S(b, g)$  is the signal generated by the MT model with parameters  $(f, D, N)$  at  $(b, g)$ .

# MT Fitting

- Constrained MT model:

$$S_{b,g}^C = f_0 e^{-bD_0} + \sum_{i=1}^3 f_i e^{-bg^t D_i g}$$

constraints: 4 compartment (1 isotropic, 3 prolate).

# MT Fitting

- Constrained MT model:

$$S_{b,g}^C = f_0 e^{-bD_0} + \sum_{i=1}^3 f_i e^{-bg^t D_i g}$$

constraints: 4 compartment (1 isotropic, 3 prolate).

- Fit by minimizing  $\sum_k (S_{b_k, g_k}^c - Y_{b_k, g_k})^2$   
where  $Y$  is the measured diffusion signal.

# Particle Swarm Optimization (PSO)

PSO is a stochastic global optimization method,

[[http://www.itm.uni-stuttgart.de/research/pso\\_opt/bilder/pso.gif](http://www.itm.uni-stuttgart.de/research/pso_opt/bilder/pso.gif)]

# Particle Swarm Optimization (PSO)

PSO is a stochastic global optimization method,

- $N_p$  random position in the parameters space (called particles),

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# Particle Swarm Optimization (PSO)

PSO is a stochastic global optimization method,

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[[http://www.itm.uni-stuttgart.de/research/pso\\_opt/bilder/pso.gif](http://www.itm.uni-stuttgart.de/research/pso_opt/bilder/pso.gif)]

# Particle Swarm Optimization (PSO)

PSO is a stochastic global optimization method,

- $N_p$  random position in the parameters space (called particles),
- Updated at every timestep by a velocity,
- Computed with information from the whole swarm of particles.

[[http://www.itm.uni-stuttgart.de/research/pso\\_opt/bilder/pso.gif](http://www.itm.uni-stuttgart.de/research/pso_opt/bilder/pso.gif)]

# PSO

- Swarm:  $\Omega_j^{t+1} = \Omega_j^t + v_j^{t+1}$

[Kennedy and Eberhart, 1995]

# PSO

- Swarm:  $\Omega_j^{t+1} = \Omega_j^t + v_j^{t+1}$
- Velocity:  $v_j^{t+1} = wv_j^t + \phi_p r_p(p_j^t - \Omega_j^t) + \phi_g r_g(g^t - \Omega_j^t)$

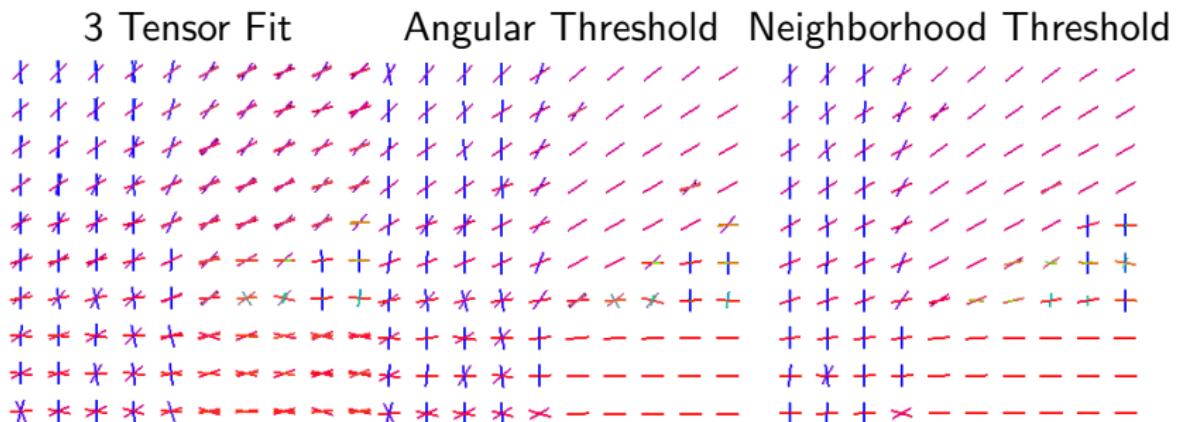
[Kennedy and Eberhart, 1995]

## PSO

- Swarm:  $\Omega_j^{t+1} = \Omega_j^t + v_j^{t+1}$
- Velocity:  $v_j^{t+1} = wv_j^t + \phi_p r_p(p_j^t - \Omega_j^t) + \phi_g r_g(g^t - \Omega_j^t)$
- where
  - $w$ ,  $\phi_p$  and  $\phi_g$  are user tuned parameters,
  - $p_j^t$  is the  $j^{th}$  particle's best known position at iteration  $t$ ,
  - $g^t$  is the swarm's best known position at iteration  $t$ ,
  - $r_p, r_g$  are uniform random variable.

[Kennedy and Eberhart, 1995]

# Model Complexity



## DSI real ODF

$$\psi_{DSI}(\hat{\mathbf{u}}) = \int_0^\infty P(r\hat{\mathbf{u}})r^2 dr$$

## Signal to Propagator relationship

$$S(\mathbf{q}) = S_0 \int P(\mathbf{r}) \exp(i2\pi\mathbf{q} \cdot \mathbf{r}) d\mathbf{r}$$

$\downarrow$

$$Q(\mathbf{r}) = S_0 P(\mathbf{r})$$

$$S(\mathbf{q}) = \int Q(\mathbf{r}) \exp(i2\pi\mathbf{q} \cdot \mathbf{r}) d\mathbf{r}$$

$\downarrow$

$$S(\mathbf{q}) = S(-\mathbf{q})$$

$$Q(\mathbf{r}) = \int S(\mathbf{q}) \exp(-2\pi\mathbf{q} \cdot \mathbf{r}) d\mathbf{q}$$

$\downarrow$

cosine transform

$$Q(\mathbf{r}) = \int S(\mathbf{q}) \cos(2\pi\mathbf{q} \cdot \mathbf{r}) \mathbf{q}$$

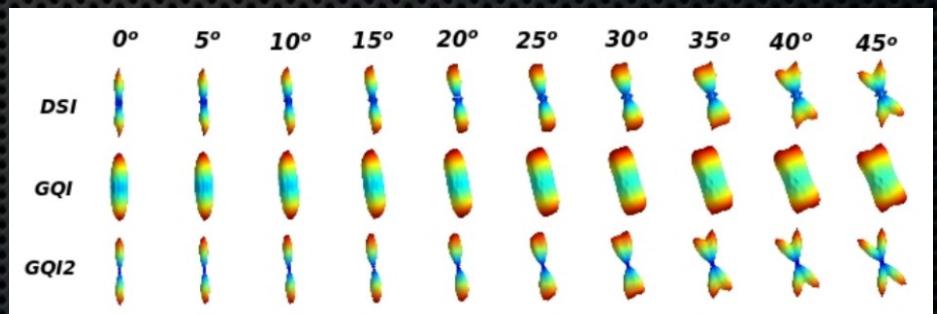
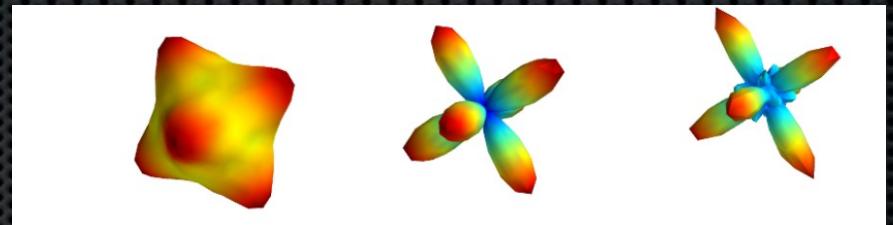
## GQI2 real ODF

$$\psi_{GQI2}(\hat{\mathbf{u}}) = \int_0^\lambda Q(r\hat{\mathbf{u}})r^2 dr$$

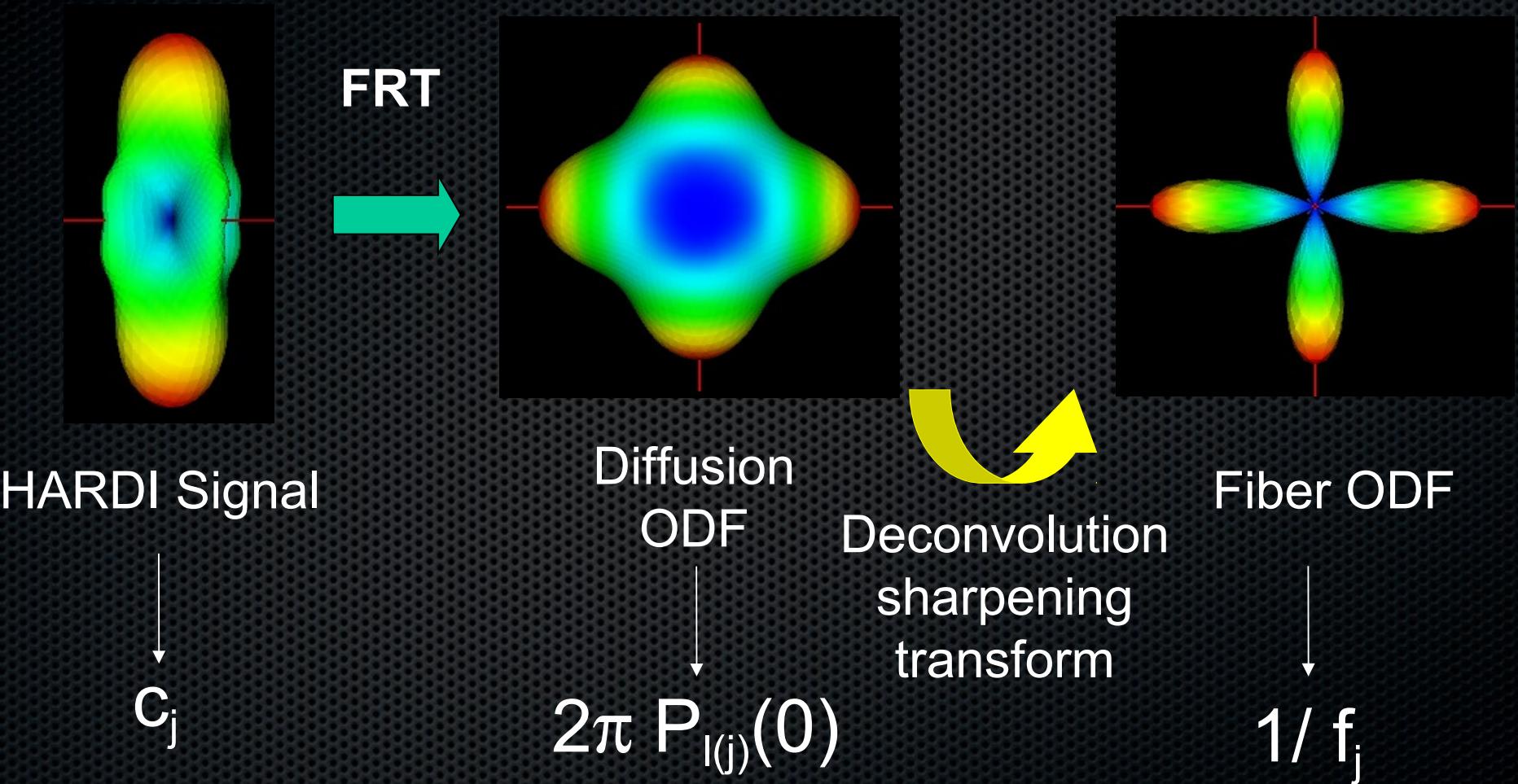
$$\psi_{GQI2}(\hat{\mathbf{u}}) = \lambda^3 \int S(\mathbf{q}) H(2\pi\lambda\mathbf{q} \cdot \hat{\mathbf{u}}) d\mathbf{q}$$

$$H(x) = \begin{cases} \frac{2 \cos(x)}{x^2} & + \frac{(x^2 - 2) \sin(x)}{x^3}, x \neq 0 \\ 1/3 & , x = 0 \end{cases}$$

GQI      GQI2      DSI

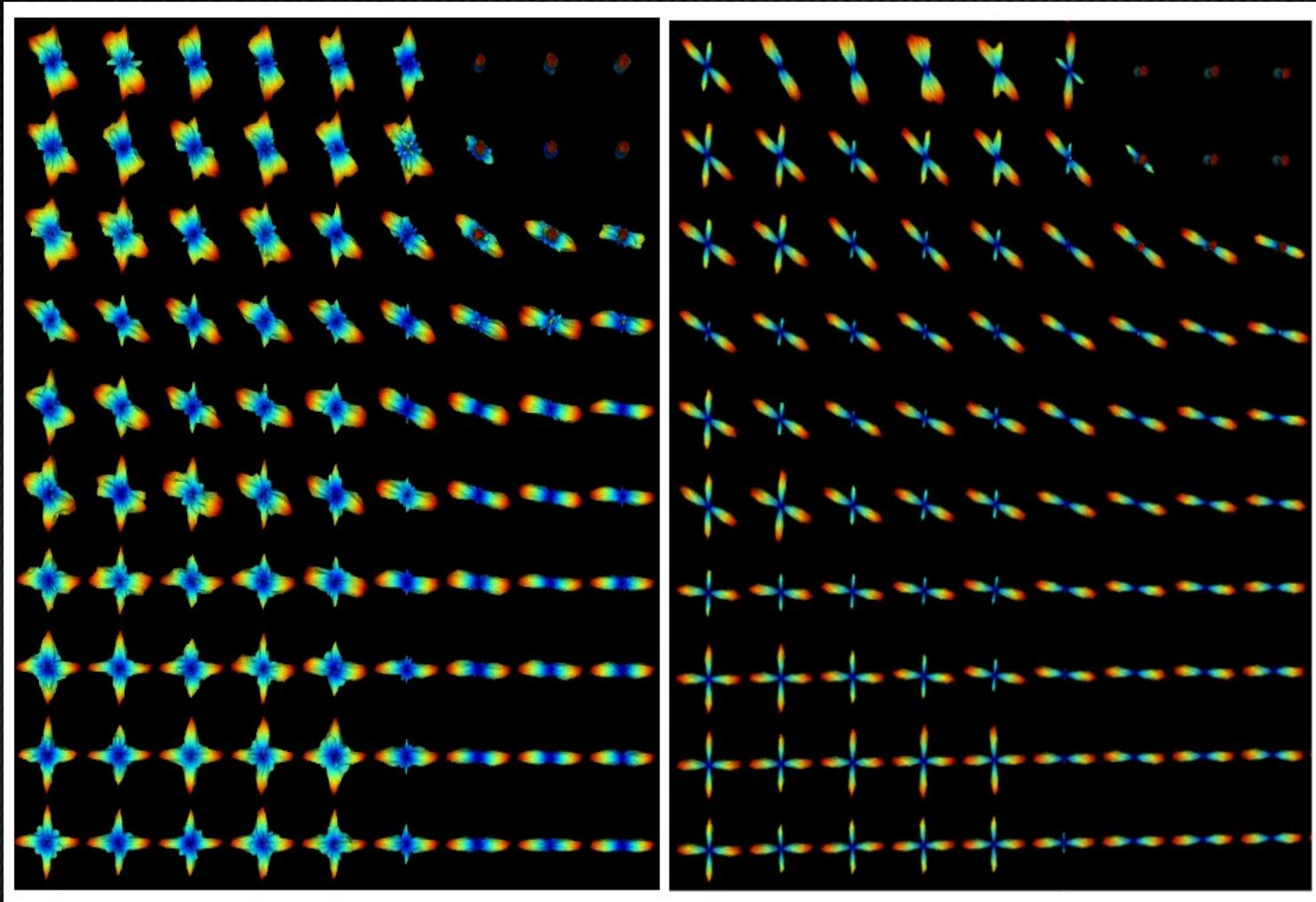


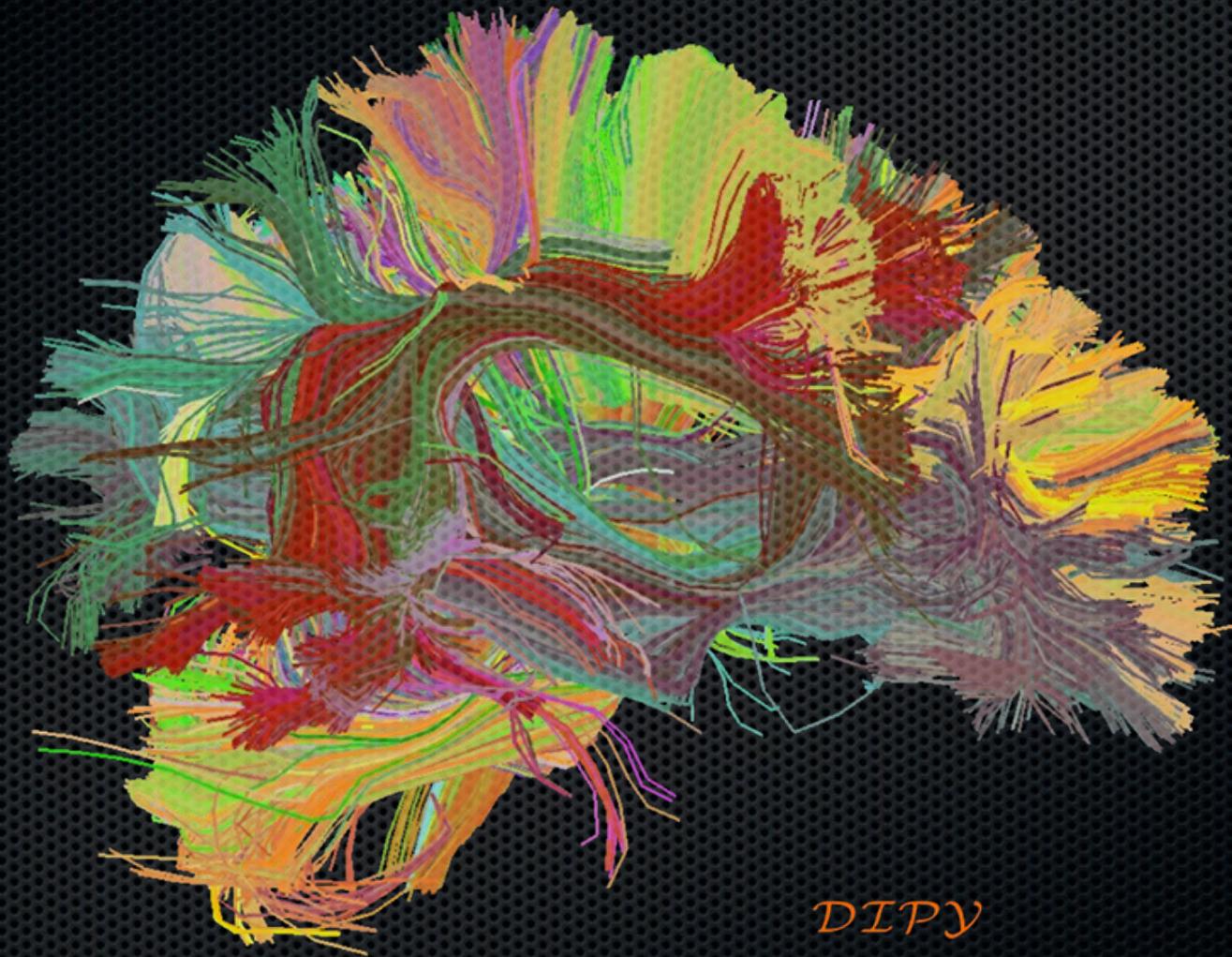
# Spherical Deconvolution Transform



# GQI2 vs GQID

(GQI2 with deconvolution)





*DIPY*

# dipy.org

Dipy — dipy 0.6.0.dev documentation - Google Chrome

dipy.org

Mendeley nipy/dipy Garyfallidis/dipy fos/fos Numpy Doc Builders REST reST2 pep8



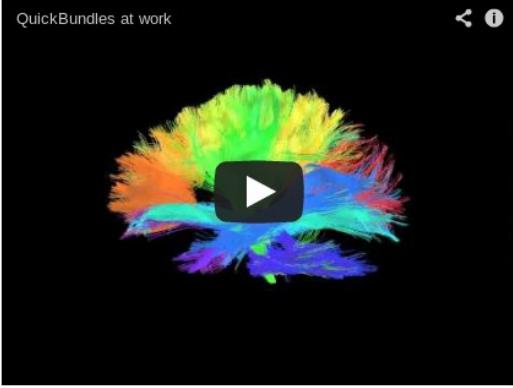
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## Diffusion Imaging In Python

Dipy is a free and open source software project for diffusion magnetic resonance imaging (dMRI) analysis.

### Highlights

In Dipy we care about methods which can solve complex problems efficiently and robustly. QuickBundles is one of the many state-of-the art algorithms found in Dipy. It can be used to simplify large datasets of streamlines. See our examples and try QuickBundles with your data [examples\\_index](#). Here is a video of QuickBundles applied on a simple dataset.



### Announcements

- Release! Version 0.6.0 21/02/2013
- Dipy 3rd Sprint, Berkeley, CA, April 2013
- ISBI 2013 will be based on Dipy, February 2013

### Getting Started

Here is a simple example showing how to calculate color\_FA. We use a

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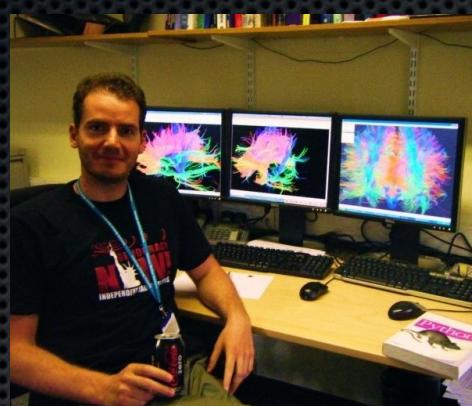
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# Dipy Developers (Core team)



Matthew  
Berkeley



Eleftherios  
Cambridge, UK



Ian  
MRC CBU Cambridge, UK



Ariel  
Stanford



Bago  
UCSF



Stefan  
South Africa

# Dipy Developers (Full list)

- Eleftherios Garyfallidis, University of Sherbrooke, QC, CA
- Ian Nimmo-Smith, MRC Cognition and Brain Sciences Unit, Cambridge, UK
- Matthew Brett, University of California, Berkeley, CA, US
- Bago Amirkbekian, University of California, San Francisco, CA, US
- Ariel Rokem, Stanford University, CA, US
- Stefan Van der Walt, Stellenbosch University, ZA
- Maxime Descoteaux, University of Sherbrooke, QC, CA
- Michael Paquette, University of Sherbrooke, QC, CA
- Christopher Nguyen, University of California, Los Angeles, CA, US
- Emanuele Olivetti, NeuroInformatics Laboratory (NILab), Trento, IT
- Yaroslav Halchenko, PBS Department, Dartmouth, NH, US
- Samuel St-Jean, University of Sherbrooke, QC, CA
- Your name here

We combine expertise in computer science, mathematics, psychology and medicine.

## Mission

The purpose of dipy is to make it easier to do better diffusion MR imaging research.

- clearly written
- clearly explained
- a good fit for the underlying ideas
- a natural home for collaboration

We hope that, if we fail to do this, you will let us know and we will try and make it better.

### Truly Open

BSD License

Documentation

Unit tests

Examples

Tutorials

Buildbots

Git/Github

Travis

### Dependencies

Numpy

Scipy

Cython

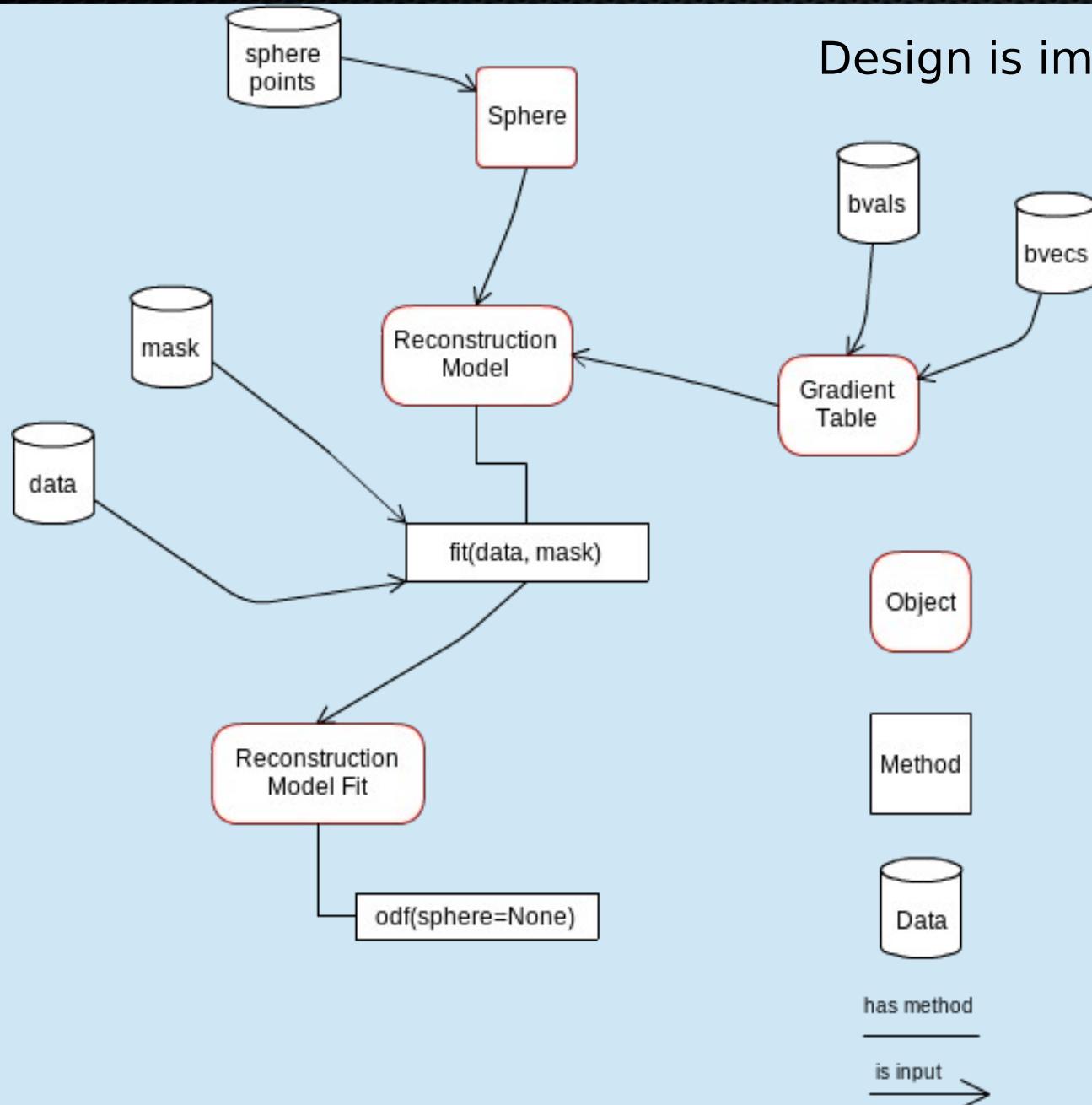
Nibabel

(Optional)

Python vtk

Pytables

# Design is important



# List of algorithms

## Reconstruction

- Diffusion Spectrum Imaging (Wedgeen)
- Generalized Q-Sampling Imaging (Yeh)
- Diffusion Spectrum Imaging with Deconvolution (Canales-Rodriguez)
- Qball (Descoteaux)
- Constant Solid Angle (Aganj)
- Opdt (Tristan-Vega)
- Diffusion Tensor (Basser)
- Simulations
- ++ CSD + MultiTensor on their way.

## Tracking

- Deterministic
- Probabilistic
- Statistics (length etc.)
- Streamline counts

## Input / Output

- nifti
- dicom (partly supported)
- trackvis
- hdf5
- fast pickling
- numpy io

# List of algorithms

## Segmentation

- QuickBundles

## Volume

- Fast volume traversal (ndindex)
- Reslice volumes

## Registration

- Warp streamlines

And your module here

Get involved and  
share some code!

Dipy 0.6 is out.

Thank you!