Neural Tractography Using an Unscented Kalman Filter

Proceedings page 126

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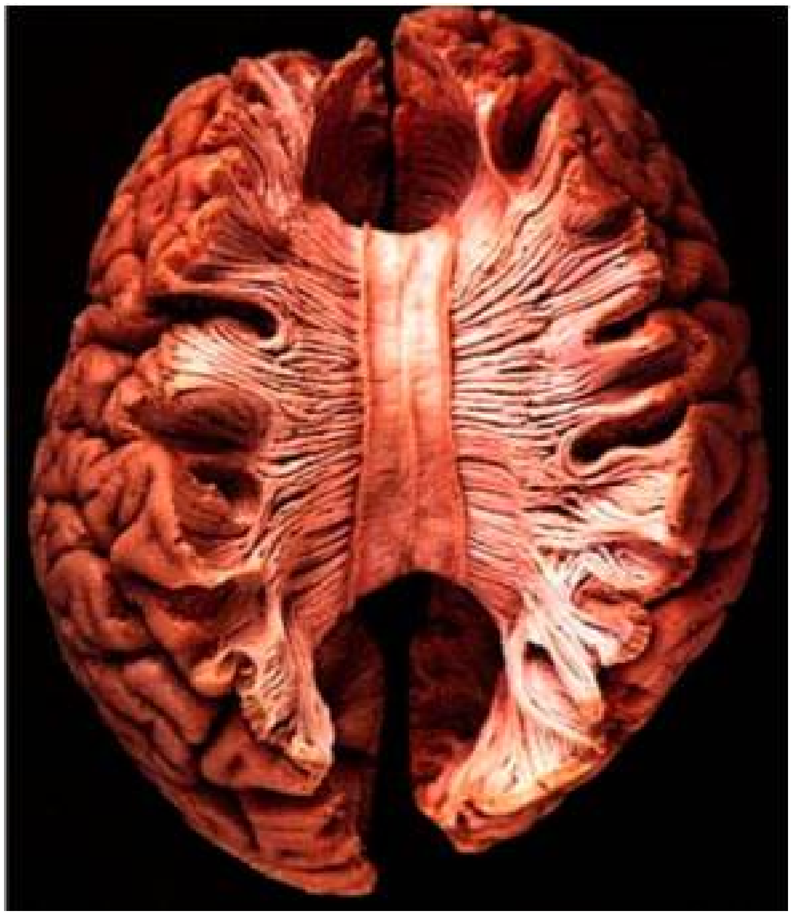
background

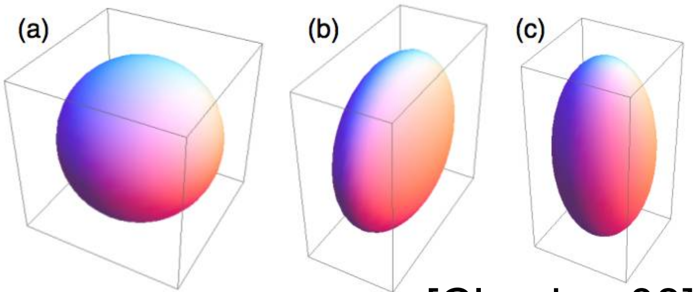
neural fibers



[Williams 97]

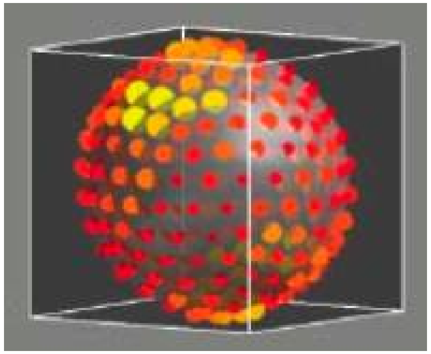
imaging techniques

- Diffusion tensor imaging (DTI)
  - [Basser 94]



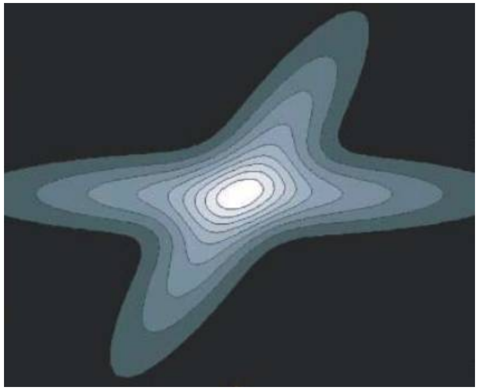
[Clayden 08]

- High Angular Resolution (QBI)
  - [Tuch 02]



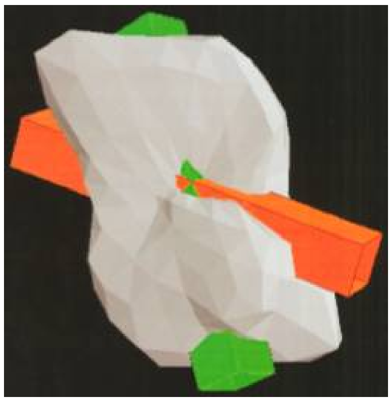
[Tuch 04]

- Diffusion Spectrum (DSI)
  - [Wedeen 05, Hagmann 05]

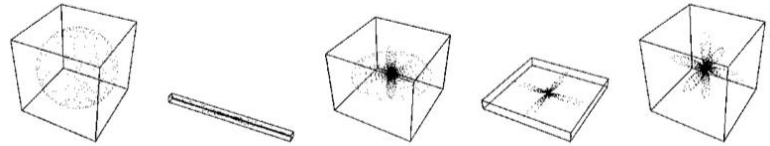


[Hagmann 05]

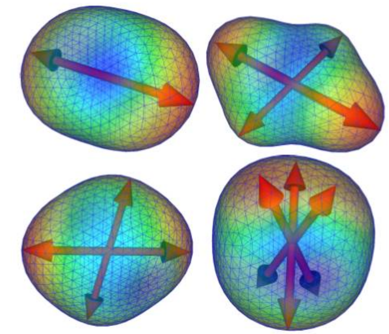
voxel reconstruction



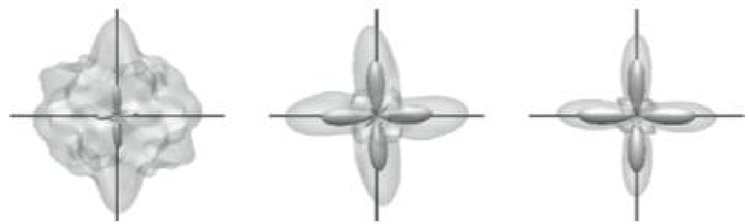
tensor mixtures [Tuch 02]



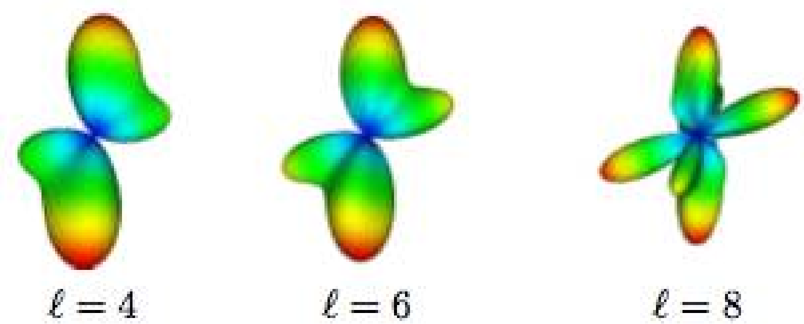
PAS [Jansons 03], MESD [Alexander 05]



HOT [Hlawitschka 05]

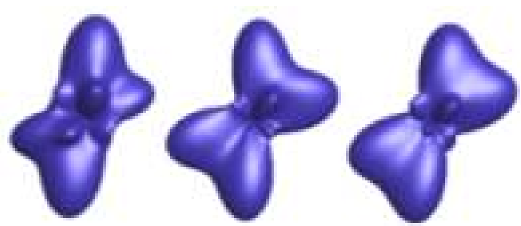


SD [Tournier 04]



spherical harmonics [Descoteaux 07]

VMF [Kumar 08]

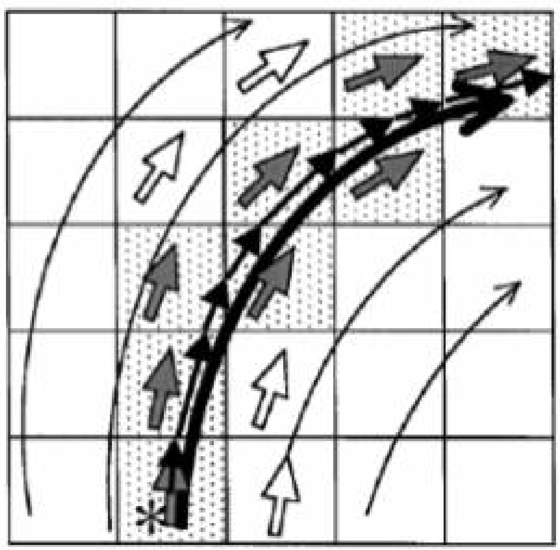


DOT [Ozarslan 05]

Wishart [Jian 07]

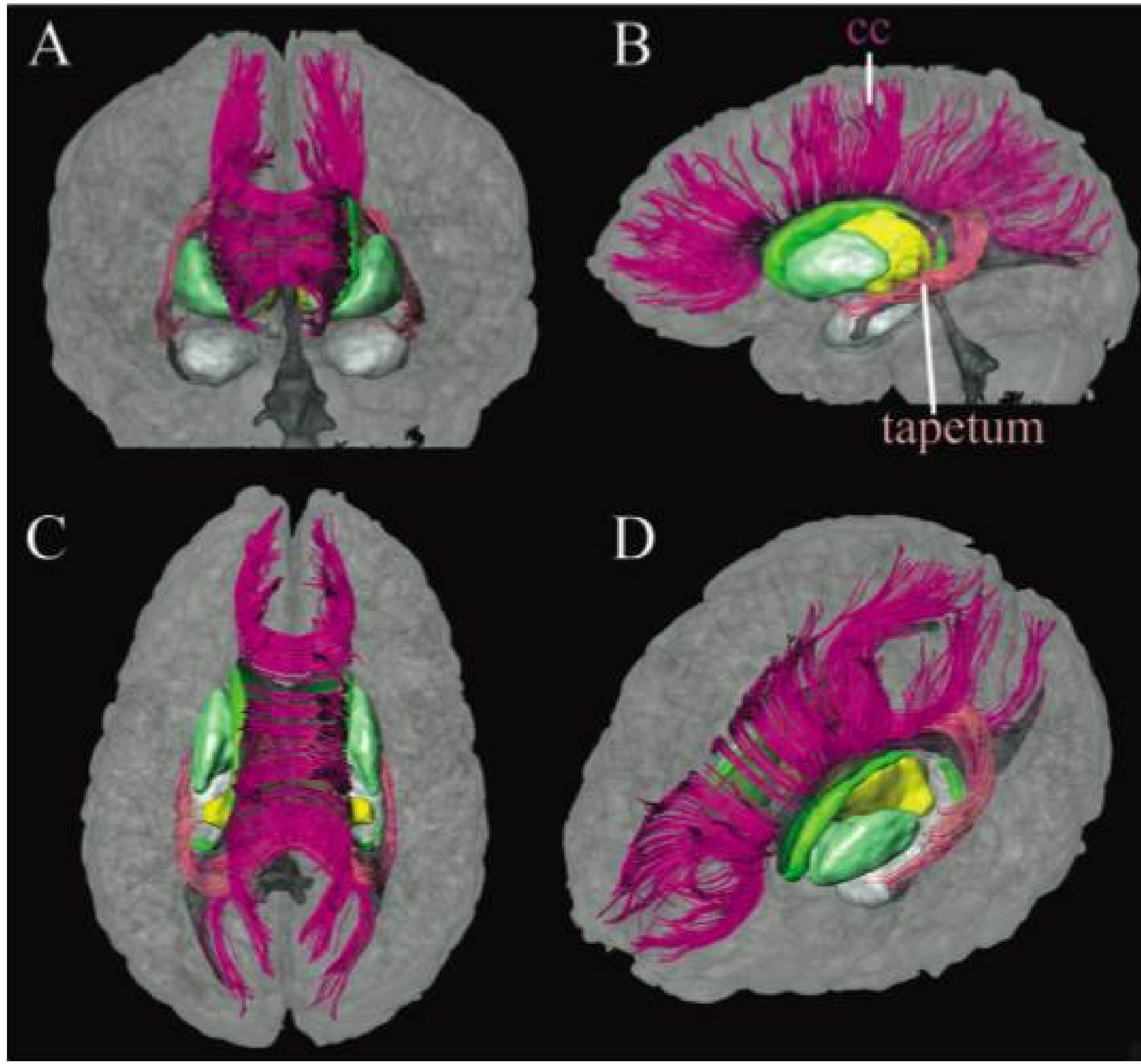
deterministic tractography

streamline



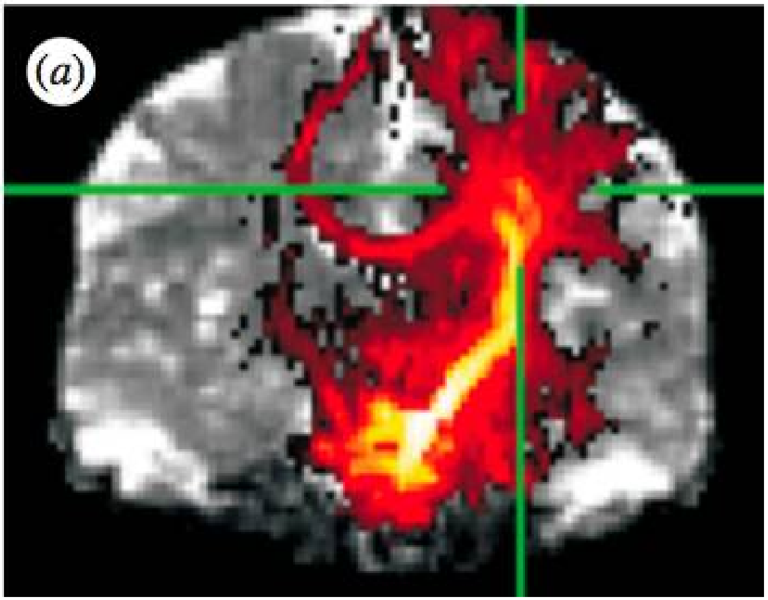
[Mori 99]

[Conturo 99, Basser 00]

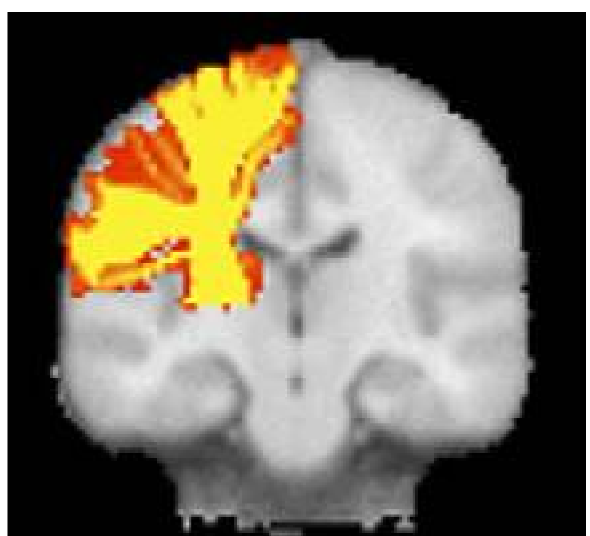


[Wakana 03]

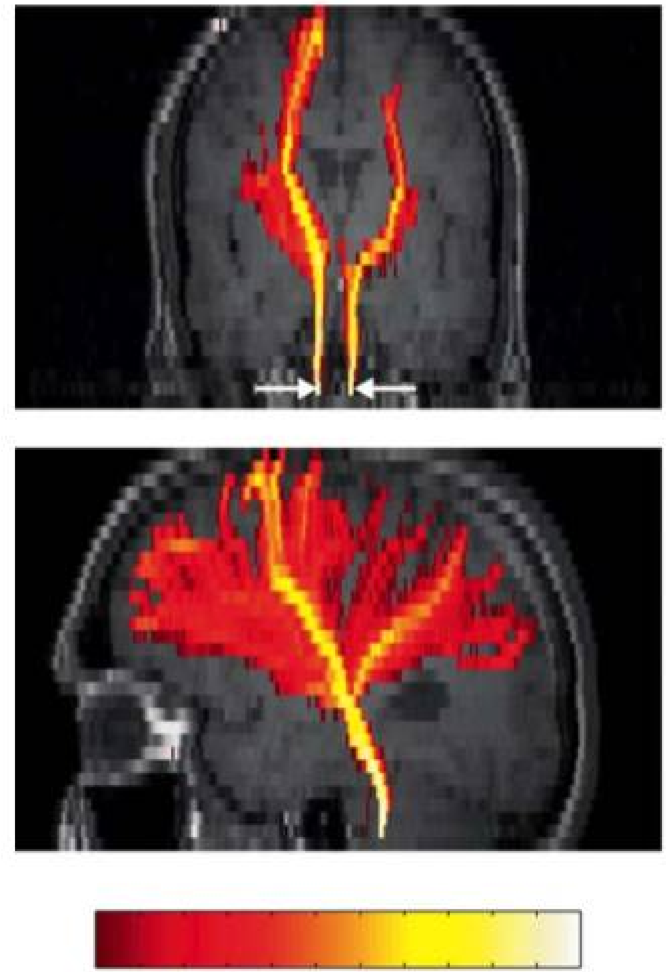
probabilistic tractography



[Parker 05]

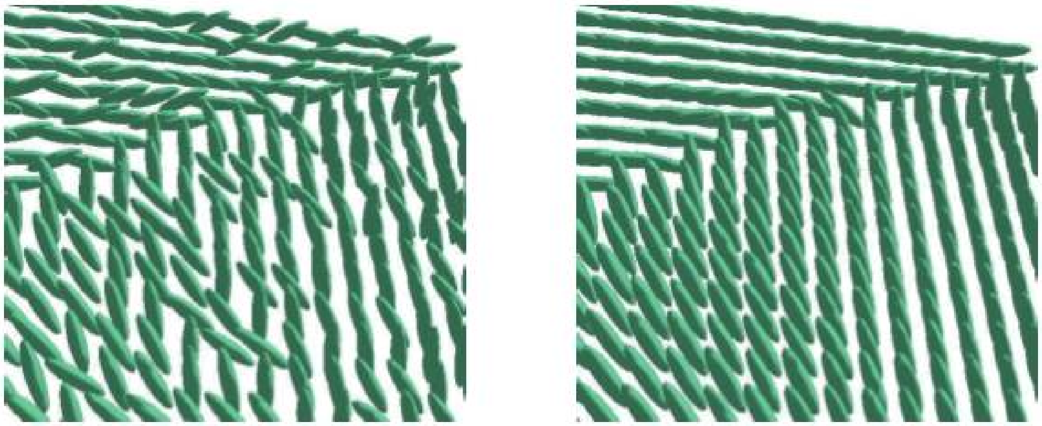


[Behrens 07]



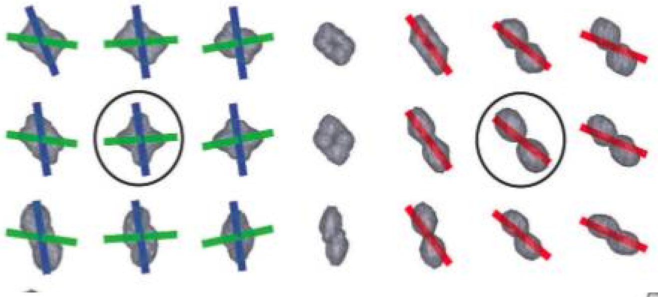
[Friman 06]

spatial regularization

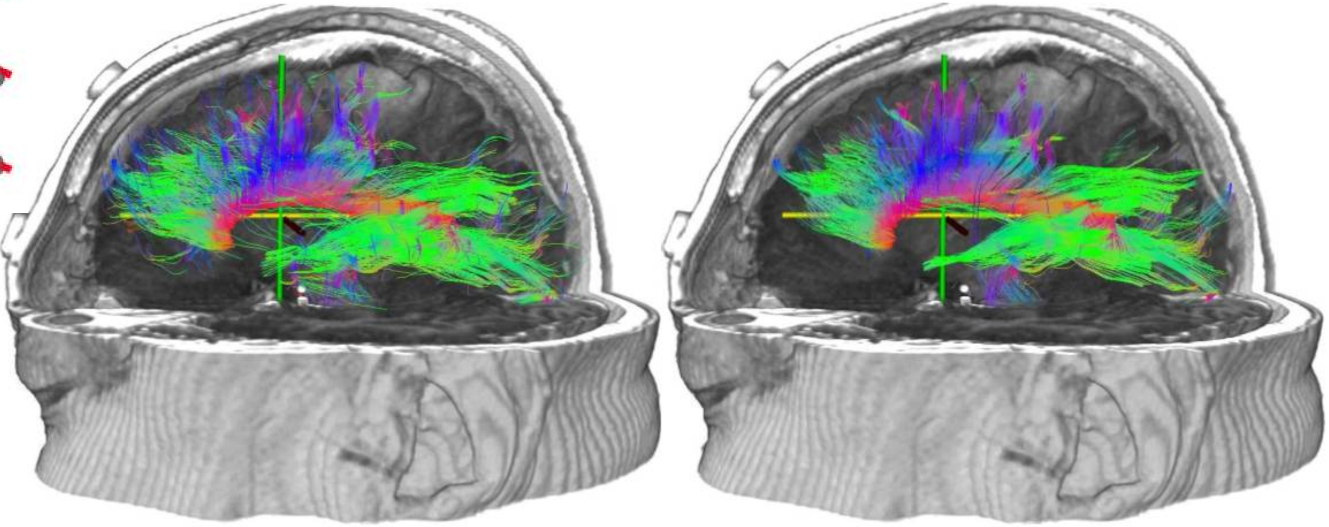


[Tschumperle 03]

pre/post-processing



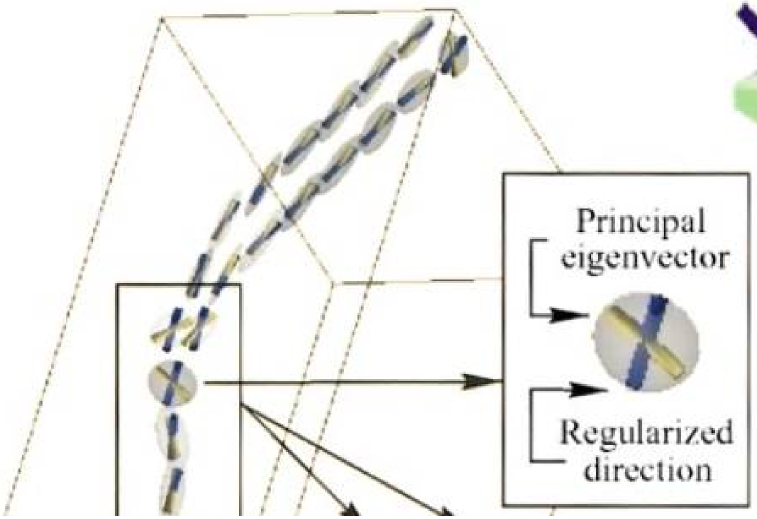
[Savadjiev 07]



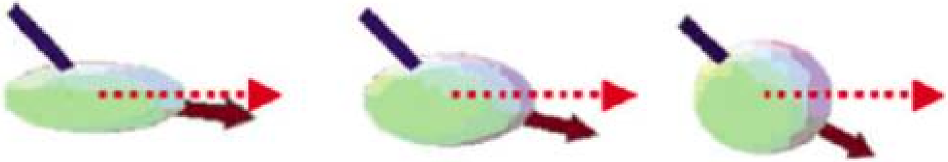
[Fillard 07]

tract regularization

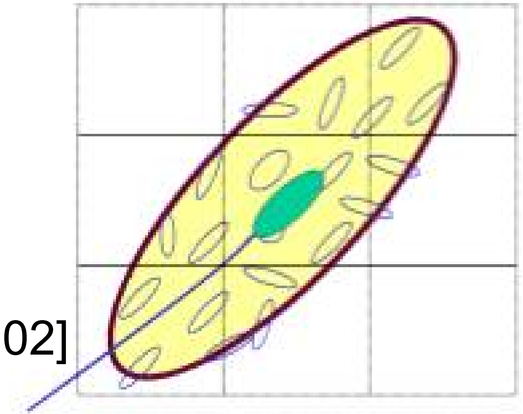
deterministic approaches:



spaghetti [Poupon 00]



deflection [Lazar 03]

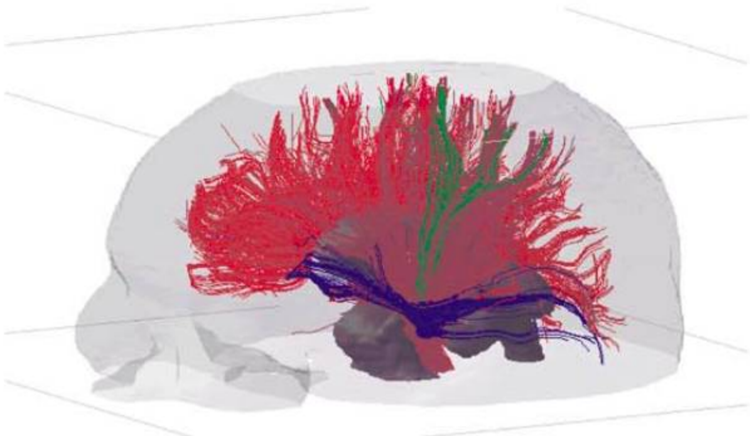


[Zhukov 02]

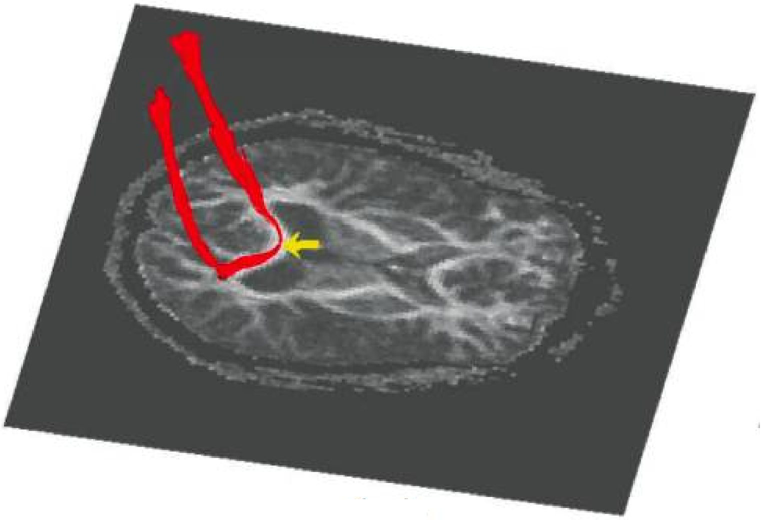
single-tensor
path regularization

tract regularization

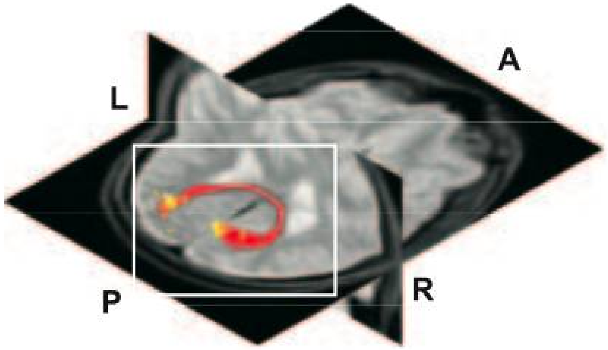
probabilistic approaches:



linear Kalman filter [Gossl 02]



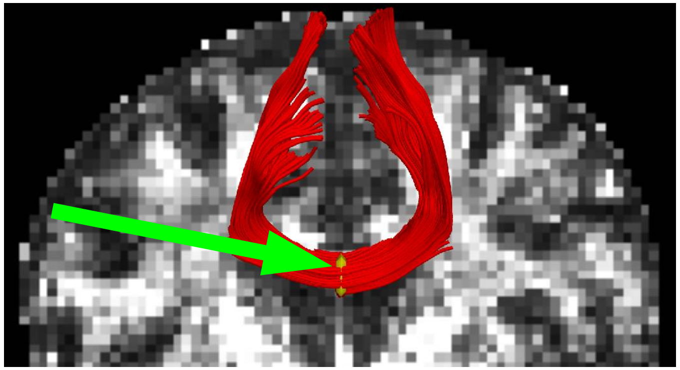
particle filtering [Zhang 07]

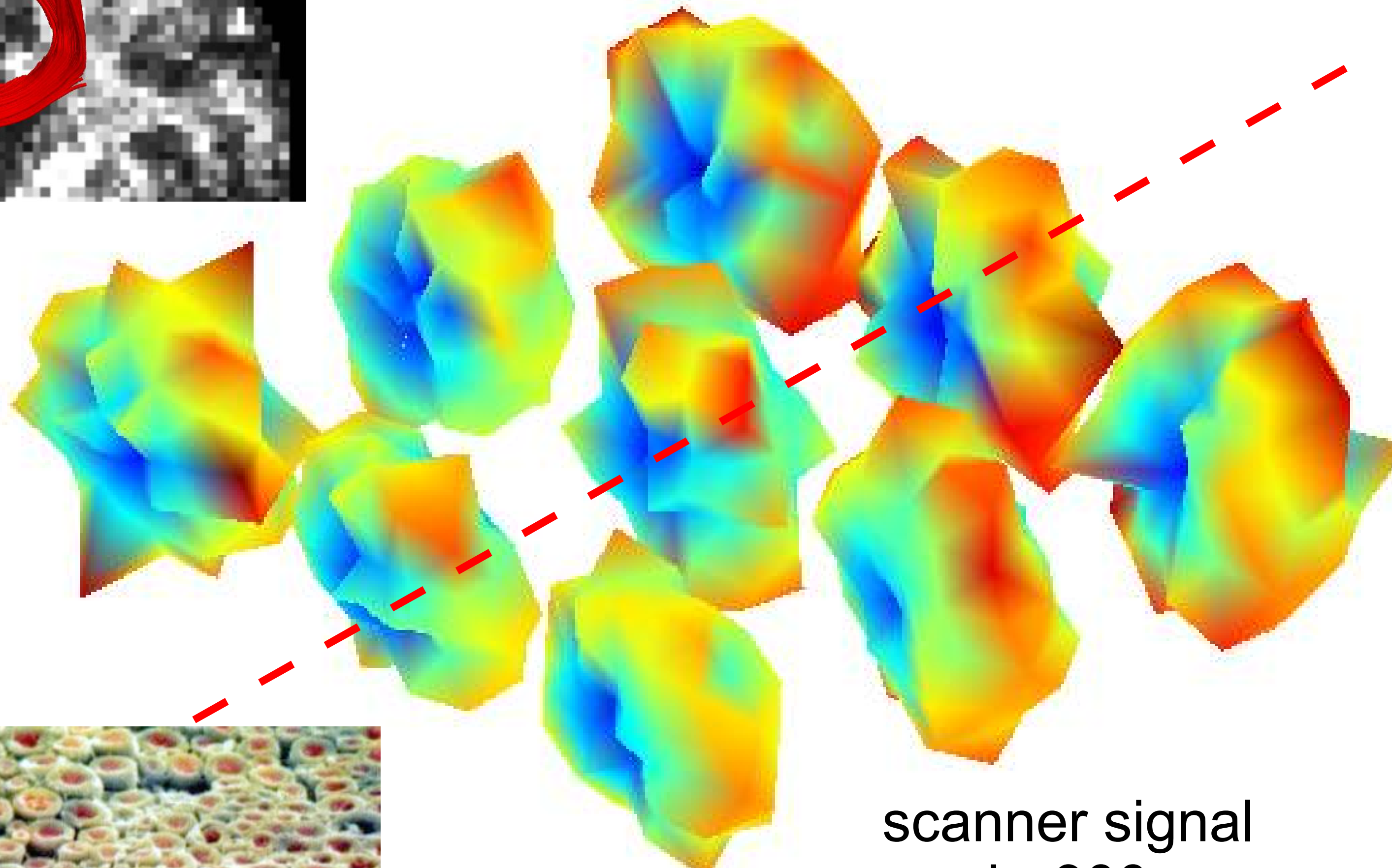


stochastic [Bjornemo 02]

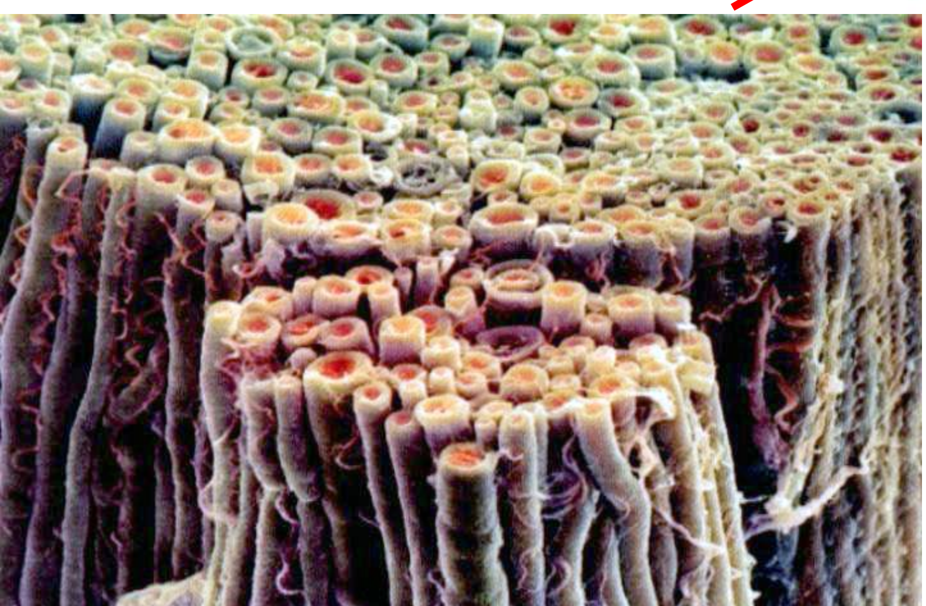
single-tensor
path regularization

method:
the model



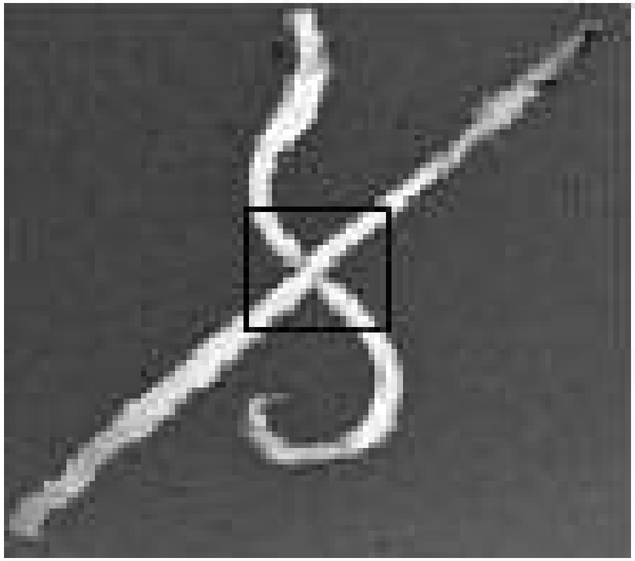


scanner signal
b=900
51 directions
1.7mm isotropic voxel
17 minute scan

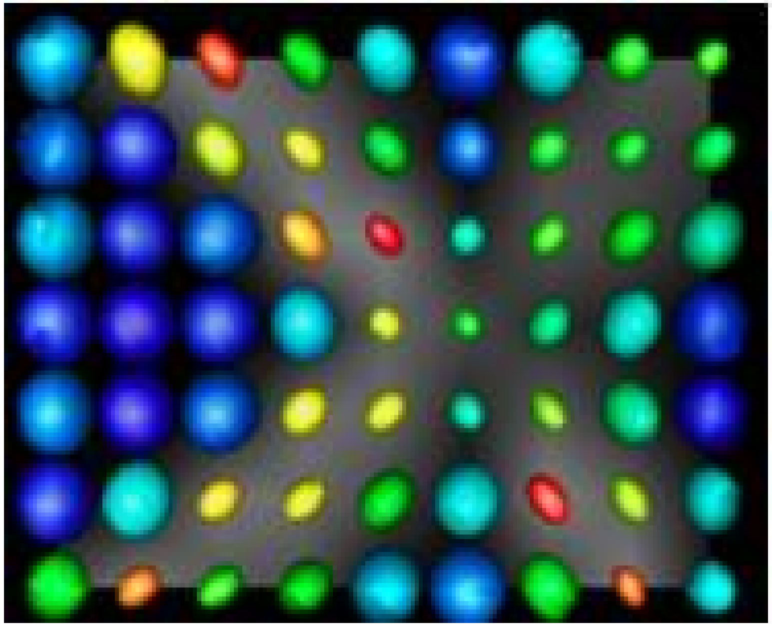


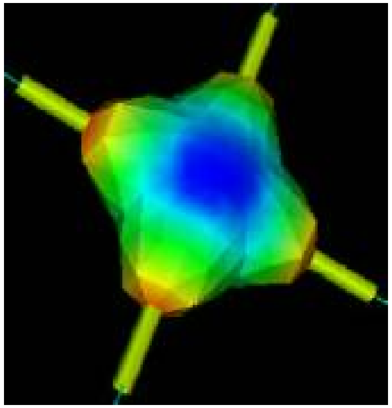
[Bartzokis]

single-tensor limitations

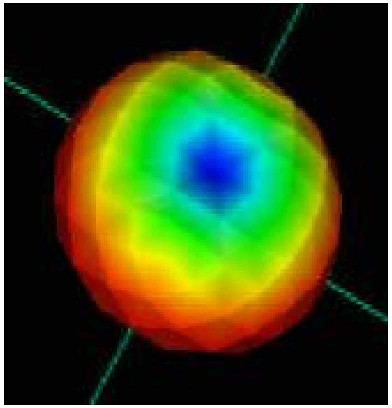


rat spinal nerves





true ODF



single-tensor ODF

[Campbell 05, Descoteaux 06]

[Descoteaux 06]

multi-tensor signal model

$$S(\boldsymbol{u}) = s_0 \sum_j w_j e^{-b \boldsymbol{u}^T D_j \boldsymbol{u}}$$

D_j	diffusion tensor
$\boldsymbol{u}$	unit direction
w_j	convex weights
b	acquisition constant
s_0	null signal (b=0)

model assumptions

...in this study

Two fibers

Fixed volume fractions

Tensors are elliptic or isotropic

model parameters

for two fibers...

...two principal directions $\boldsymbol{m} \in \mathbb{R}^3$

...two primary eigenvalues $\lambda_1 \in \mathbb{R}$

...two minor eigenvalues $\lambda_2 \in \mathbb{R}$

5 + 5 = 10 parameters

model parameters

for two fibers...

...two principal directions $\boldsymbol{m} \in \mathbb{R}^3$

...two primary eigenvalues $\lambda_1 \in \mathbb{R}$

...two minor eigenvalues $\lambda_2 \in \mathbb{R}$

5 + 5 = 10 parameters

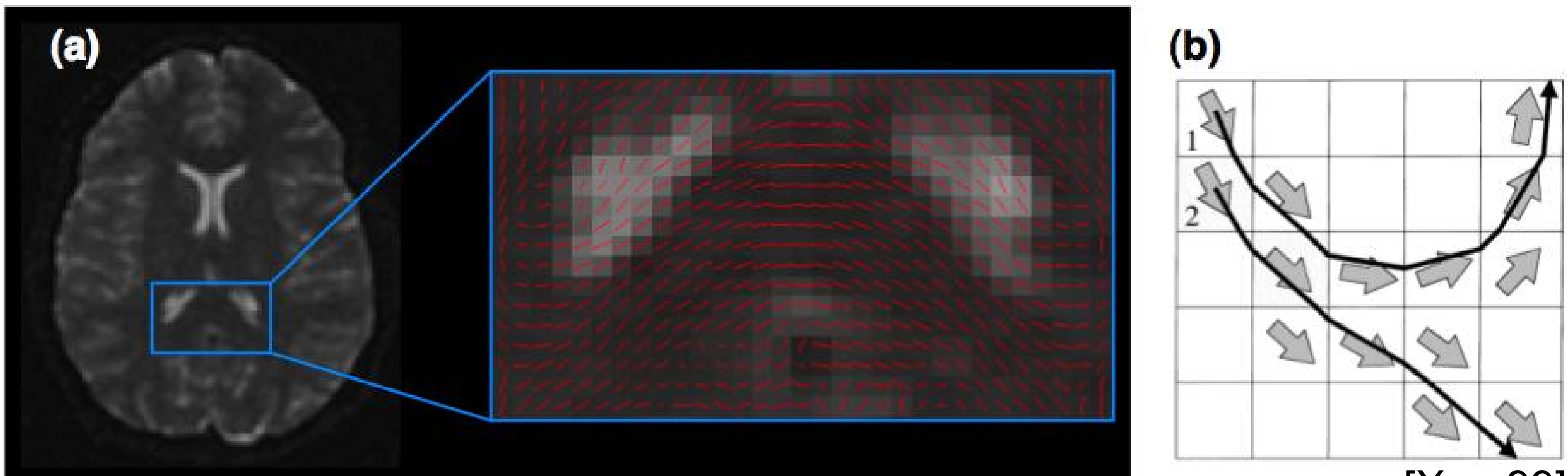
$$S(\boldsymbol{u}) = 0.5\, s_0 e^{-b \boldsymbol{u}^T D_1 \boldsymbol{u}} + 0.5\, s_0 e^{-b \boldsymbol{u}^T D_2 \boldsymbol{u}}$$

$$D_1 = \lambda_{11} \boldsymbol{m}_1 \boldsymbol{m}_1^T + \lambda_{21} (\boldsymbol{p}\,\boldsymbol{p}^T + \boldsymbol{q}\,\boldsymbol{q}^T)$$

eigenvectors: $\boldsymbol{m}, \boldsymbol{p}, \boldsymbol{q}$

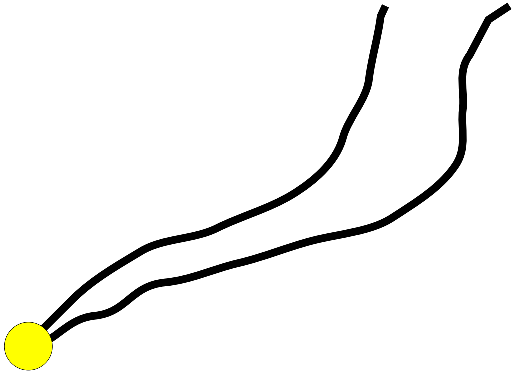
method:
estimating the model

independent estimation

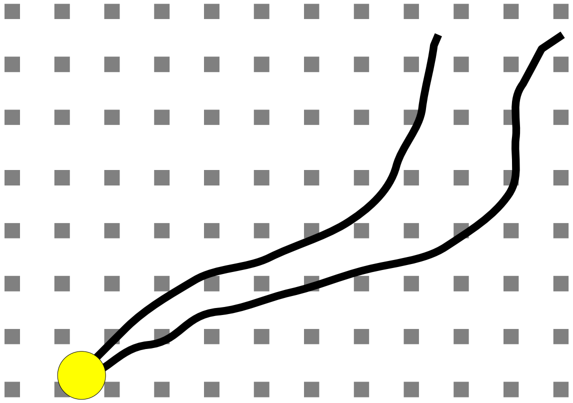


[Xue 99]

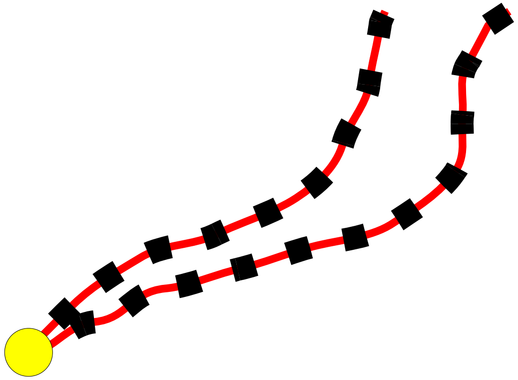
the system: a fiber



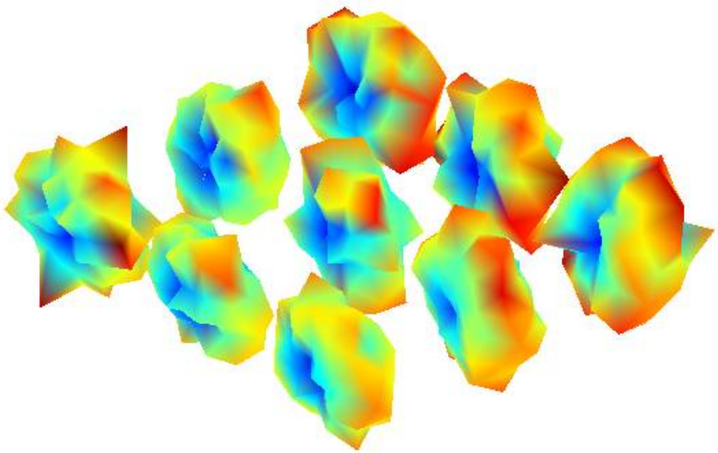
independent process



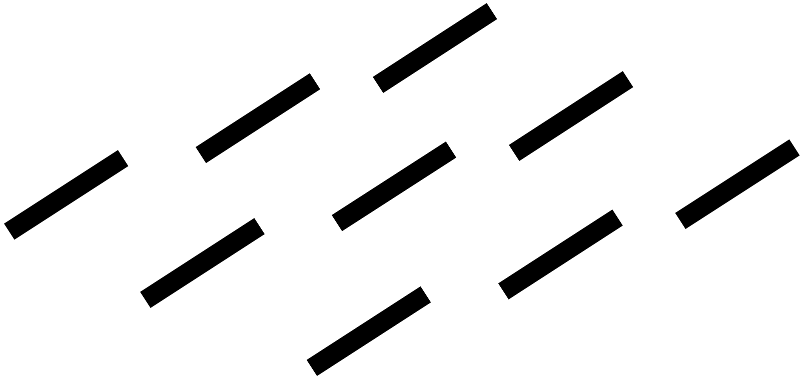
causal process



model-based filtering



scanner measurement



underlying model

objectives:

- estimate model from measurements
- suppress noise

notation

$\boldsymbol{x}_t$ state of system at time t

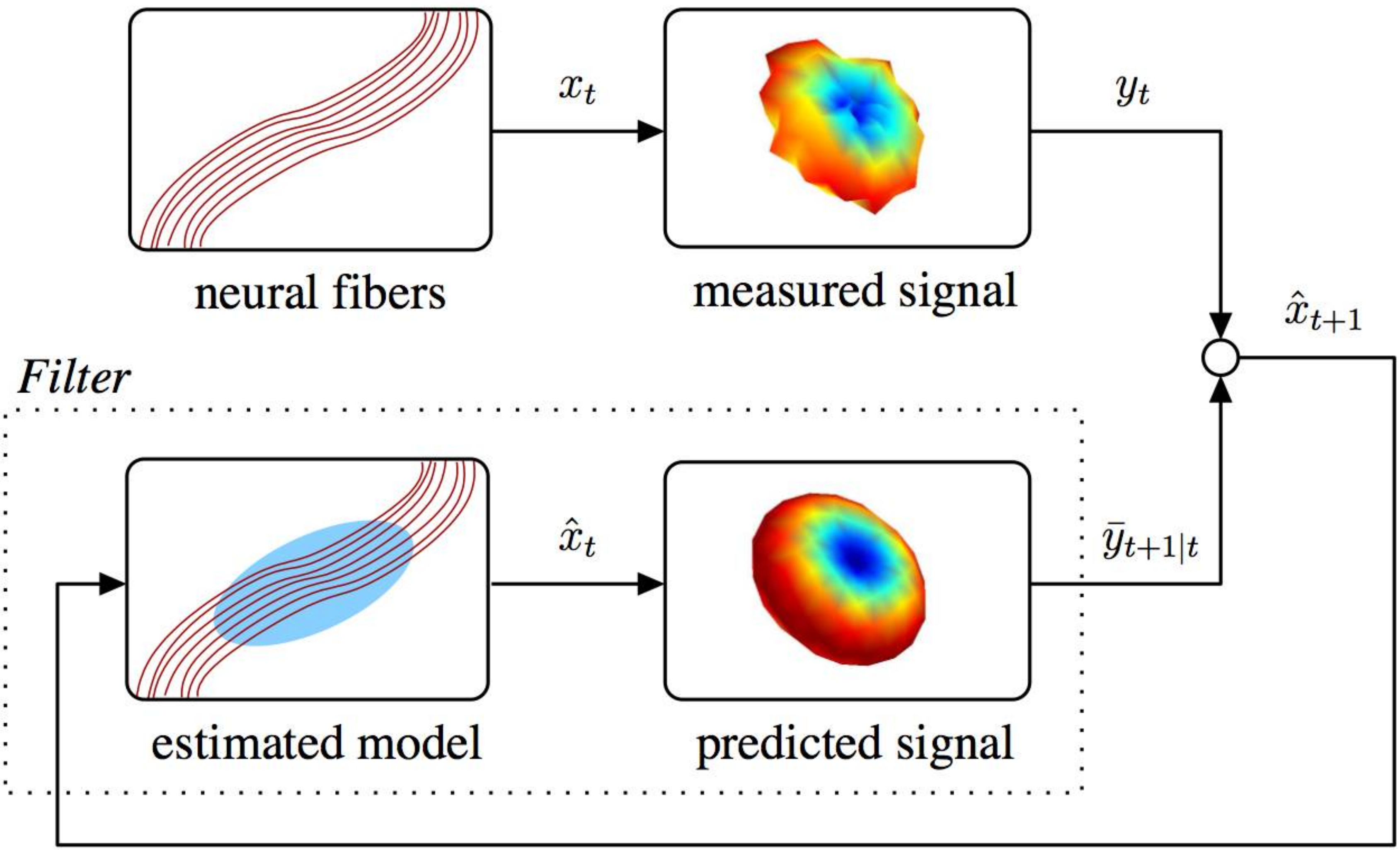
state = “model parameters”

$\boldsymbol{y}_t$ what you see at time t

observation, measurement

	linear	nonlinear
update:	$\boldsymbol{x}_{t+1} = F\,\boldsymbol{x}_t$	$\boldsymbol{x}_{t+1} = f(\boldsymbol{x}_t)$
observation:	$\boldsymbol{y}_t = G\,\boldsymbol{x}_t$	$\boldsymbol{y}_t = g(\boldsymbol{x}_t)$

Kalman filtering



predict … measure … reconcile … repeat ...

$$\boldsymbol{x} = [\,\boldsymbol{m}_1\,\lambda_{11}\,\lambda_{12}\,\boldsymbol{m}_2\,\lambda_{21}\,\lambda_{22}\,]^T \in R^{10}$$

10 dimensional state

$\boldsymbol{y} \in R^m$ signal

$$\boldsymbol{x} = [\boldsymbol{m}_1 \lambda_{11} \lambda_{12} \boldsymbol{m}_2 \lambda_{21} \lambda_{22}]^T \in R^{10}$$

10 dimensional state

$\boldsymbol{y} \in R^m$ signal

$$\boldsymbol{x}_{t+1} = f(\boldsymbol{x}_t) = \boldsymbol{x}_t$$

small steps
slowly varying state

$$\boldsymbol{y}_t = g(\boldsymbol{x}_t) = S(\boldsymbol{u})$$

$$\boldsymbol{x} = [\boldsymbol{m}_1 \lambda_{11} \lambda_{12} \boldsymbol{m}_2 \lambda_{21} \lambda_{22}]^T \in R^{10}$$

10 dimensional state

$$\boldsymbol{y} \in R^m$$ signal

$$\boldsymbol{x}_{t+1} = f(\boldsymbol{x}_t) = \boldsymbol{x}_t$$

small steps
slowly varying state

$$\boldsymbol{y}_t = g(\boldsymbol{x}_t) = S(\boldsymbol{u})$$

$$y(\boldsymbol{u}) = S(\boldsymbol{u}) = 0.5\, s_0 e^{-b \boldsymbol{u}^T D_1 \boldsymbol{u}} + 0.5\, s_0 e^{-b \boldsymbol{u}^T D_2 \boldsymbol{u}}$$

$$D = \lambda_1 \boldsymbol{m} \boldsymbol{m}^T + \lambda_2 (\boldsymbol{p} \boldsymbol{p}^T + \boldsymbol{q} \boldsymbol{q}^T)$$

signal reconstruction is nonlinear

independent optimization

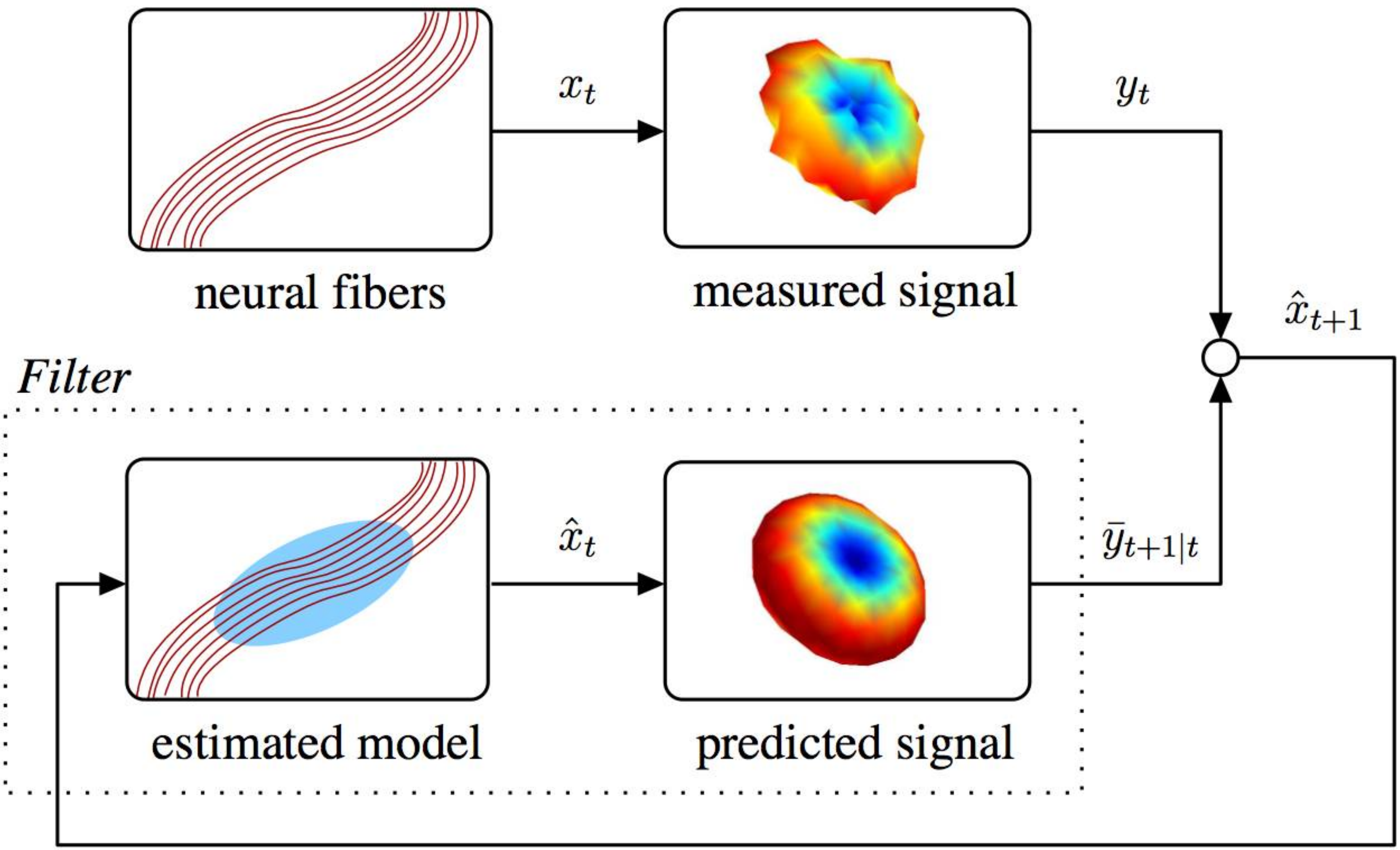
- least squares
  linearization
- gradient descent
  local minima
- Levenberg-Marquardt
  local minima

causal estimation

- extended Kalman filter
  mean + covariance
  linearization
- particle filter
  non-parametric
  sampling
- unscented Kalman filter
  mean + covariance
  no linearization
  limited sampling

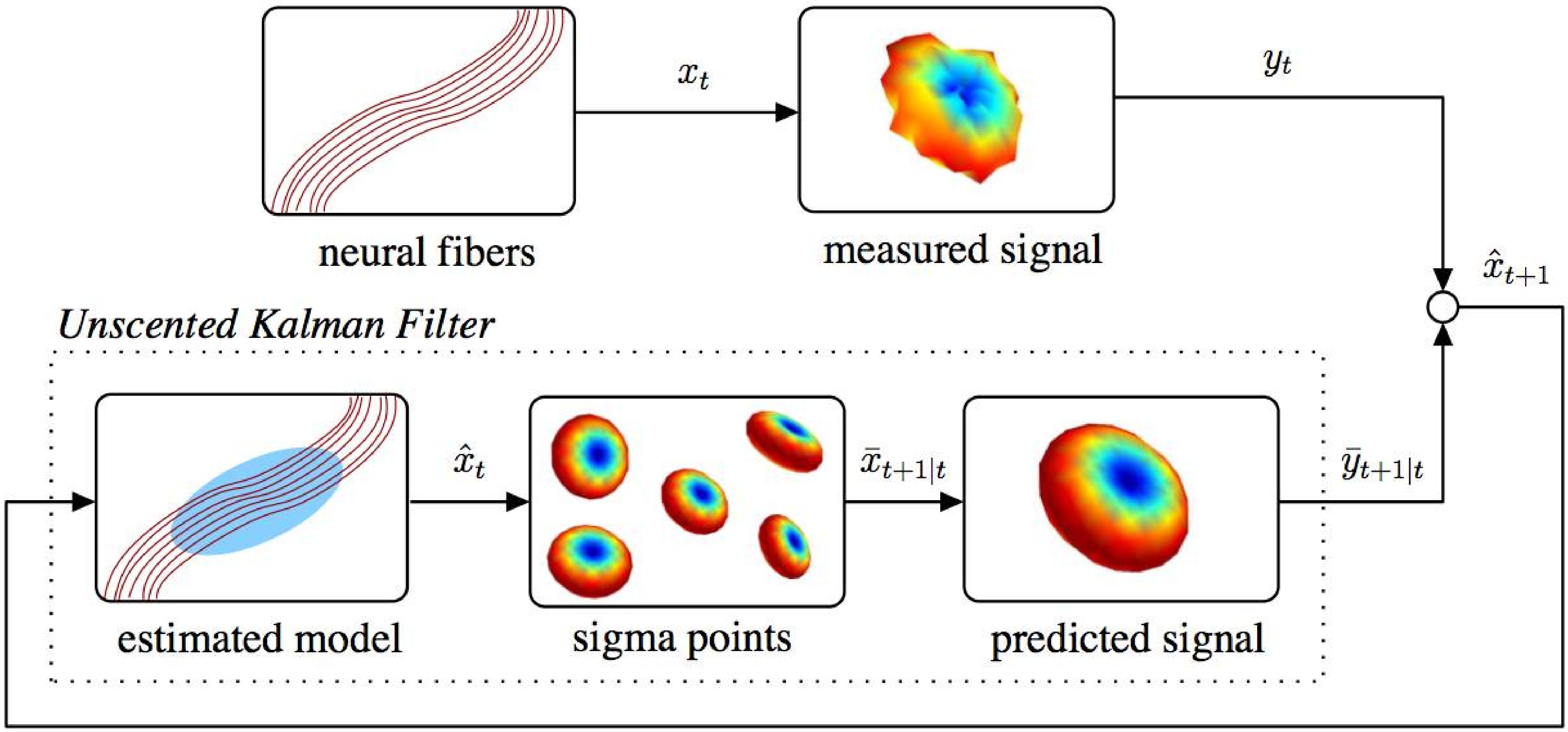
[Julier 04, Merwe 03]

linear Kalman filter



predict … measure … reconcile … repeat ...

unscented Kalman filter

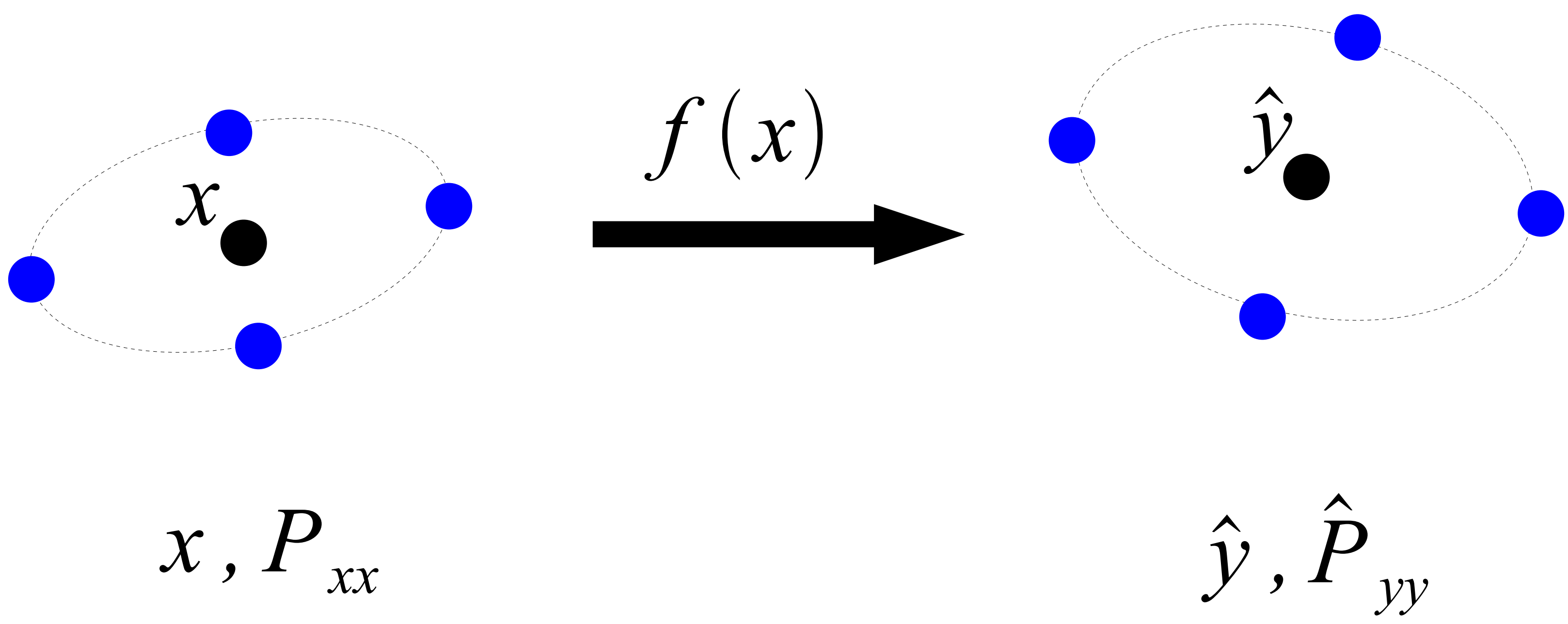


same update equations

modified prediction step

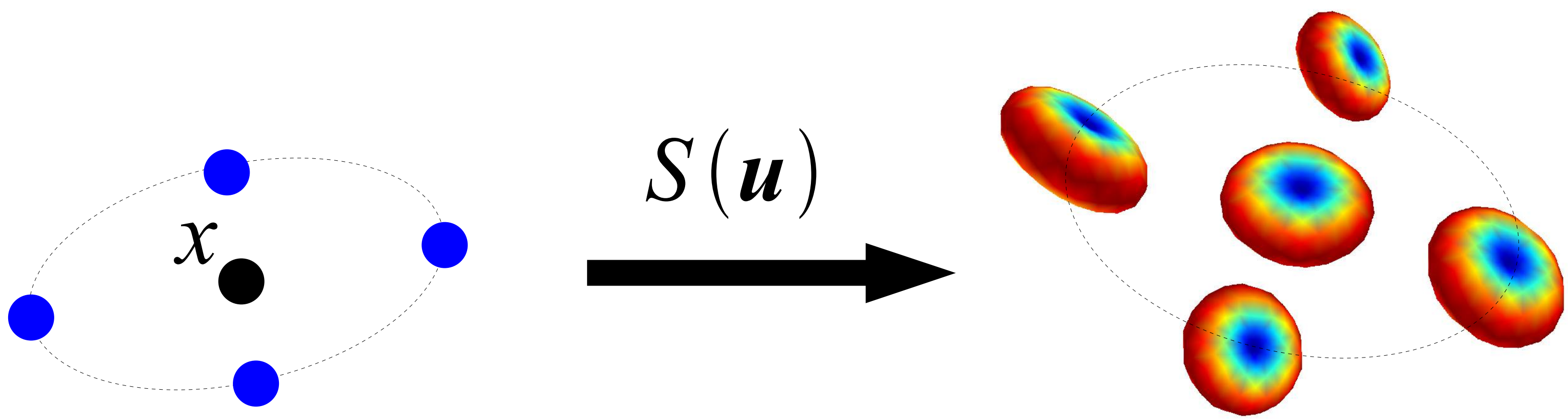
unscented transform

approximate the statistics...not the function



unscented transform

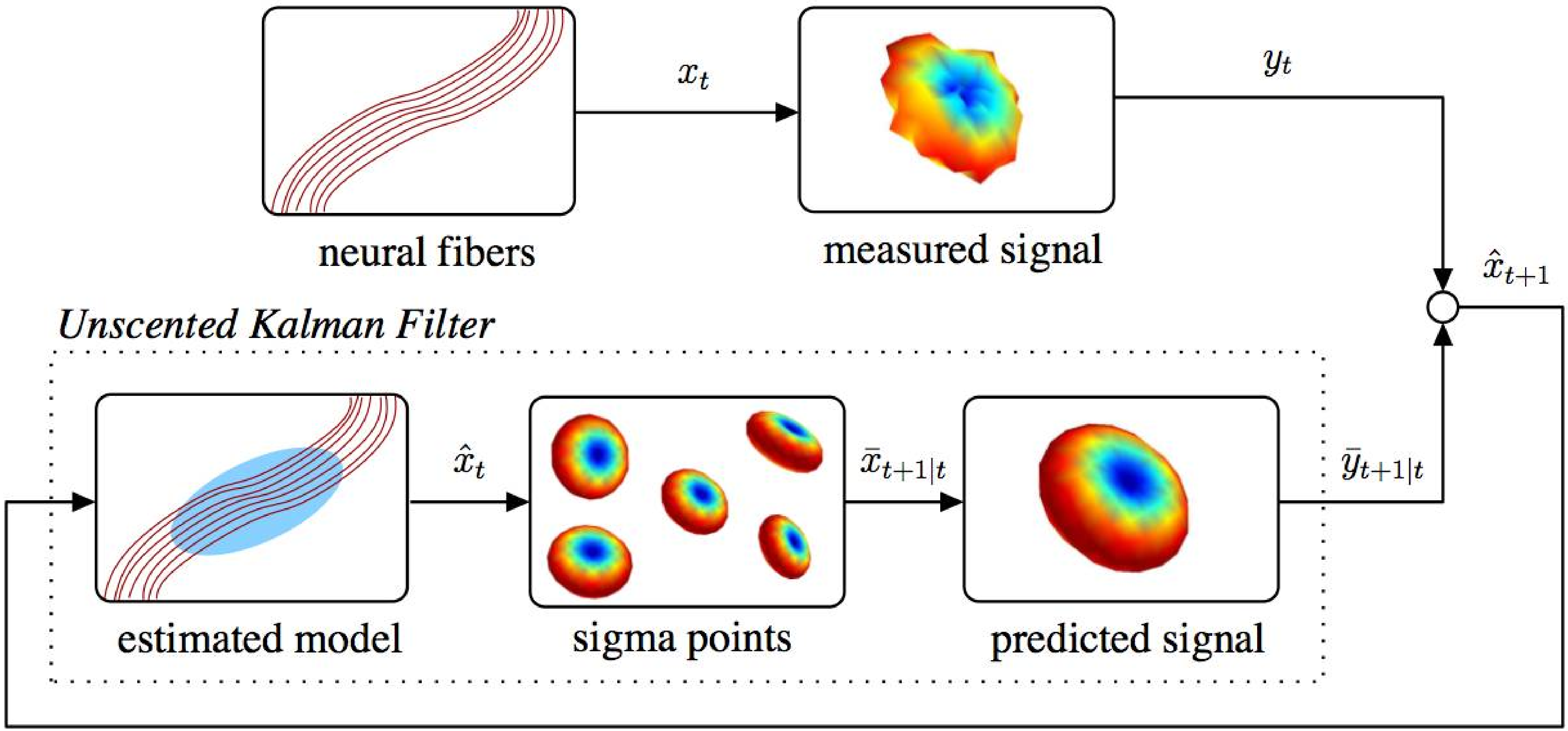
for signal reconstruction...



$x\,,\,P_{xx}$ $\qquad$ $\hat{y}\,,\,\hat{P}_{yy}$

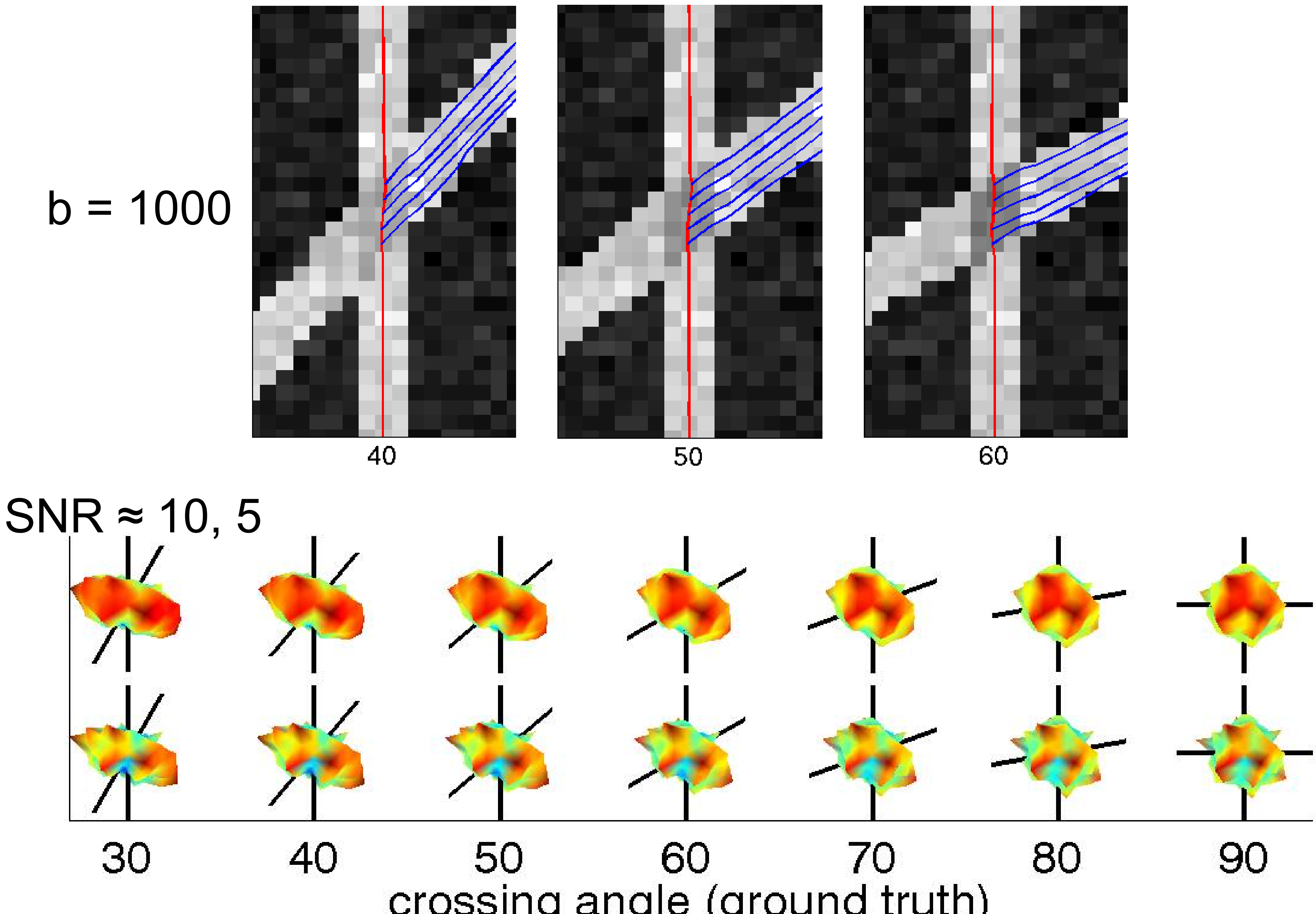
$$x = [\,\boldsymbol{m}_1\,\lambda_{11}\,\lambda_{12}\,\boldsymbol{m}_2\,\lambda_{21}\,\lambda_{22}\,]^T$$

unscented Kalman filter



predict … measure … reconcile … repeat ...

synthetic validation



b = 1000
40
50
60
SNR ≈ 10, 5
30
40
50
60
70
80
90
crossing angle (ground truth)

brute force optimization

- matching pursuit
- parametric dictionary
- noiseless signal
- discretization, noise

spherical harmonics

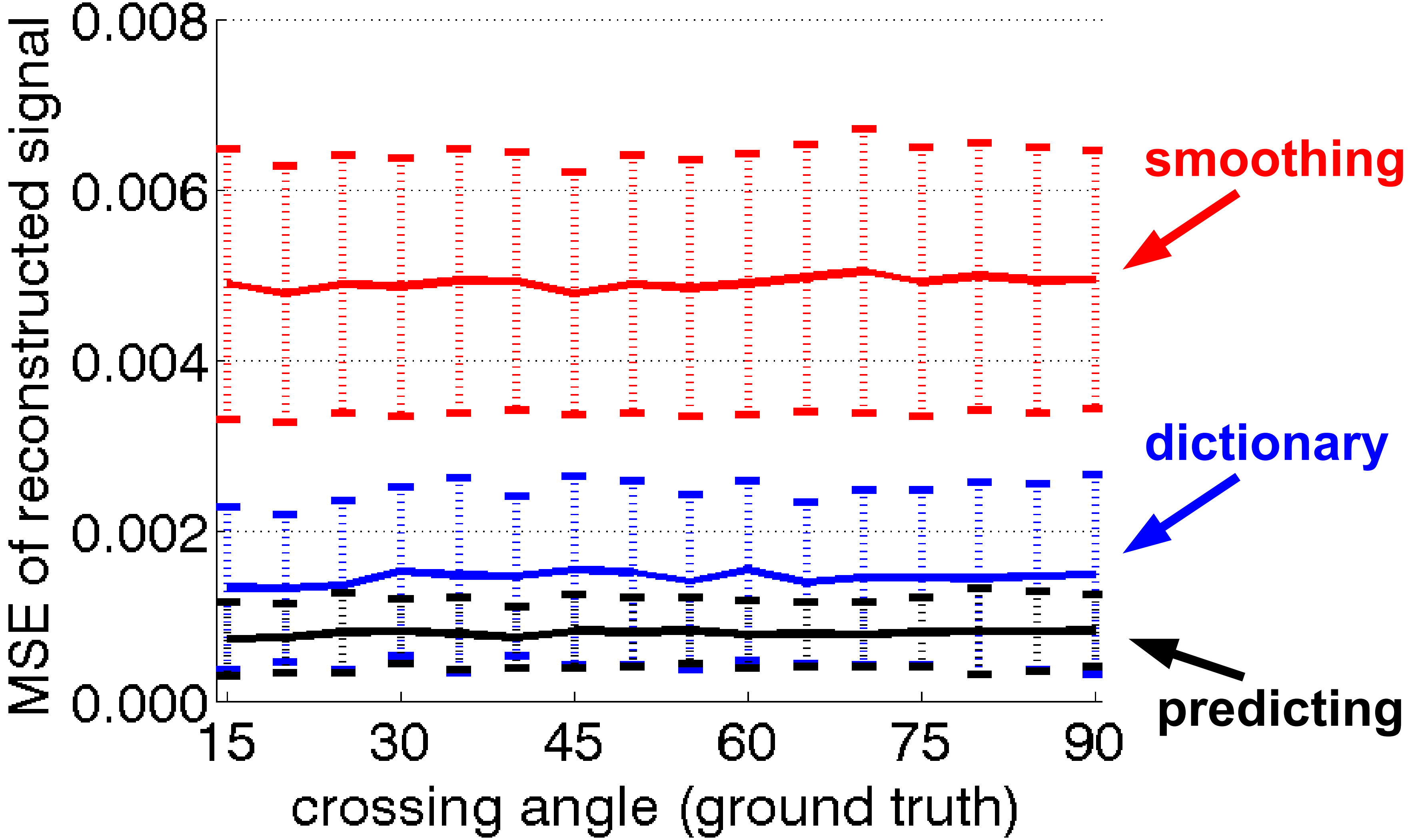
- non-parametric
- order eight (8)
- fiber sharpening for peak detection (L=0.006)

[Descoteaux 07]

filtered tractography

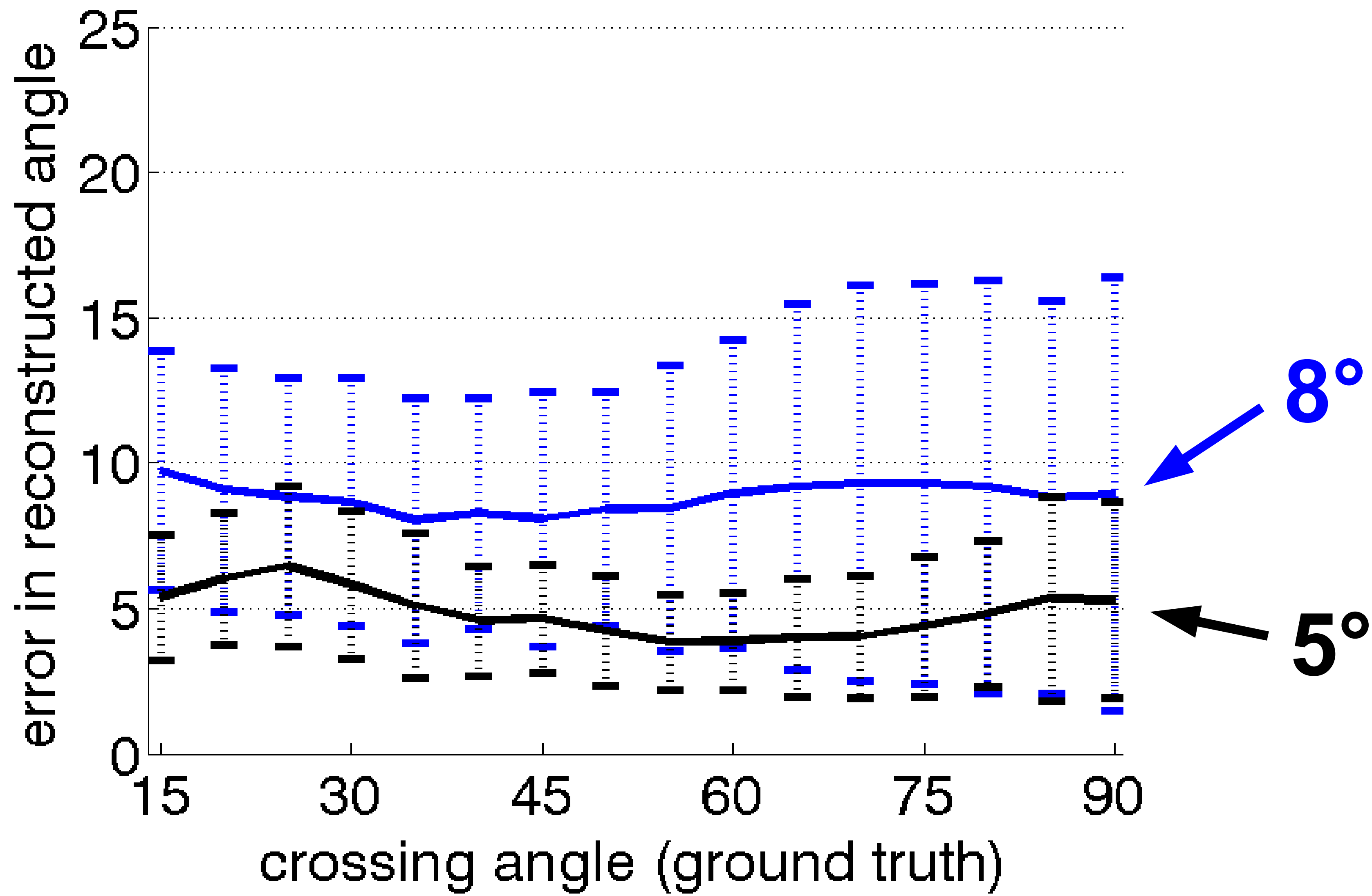
- two-fiber model
- unscented Kalman filter

signal reconstruction error



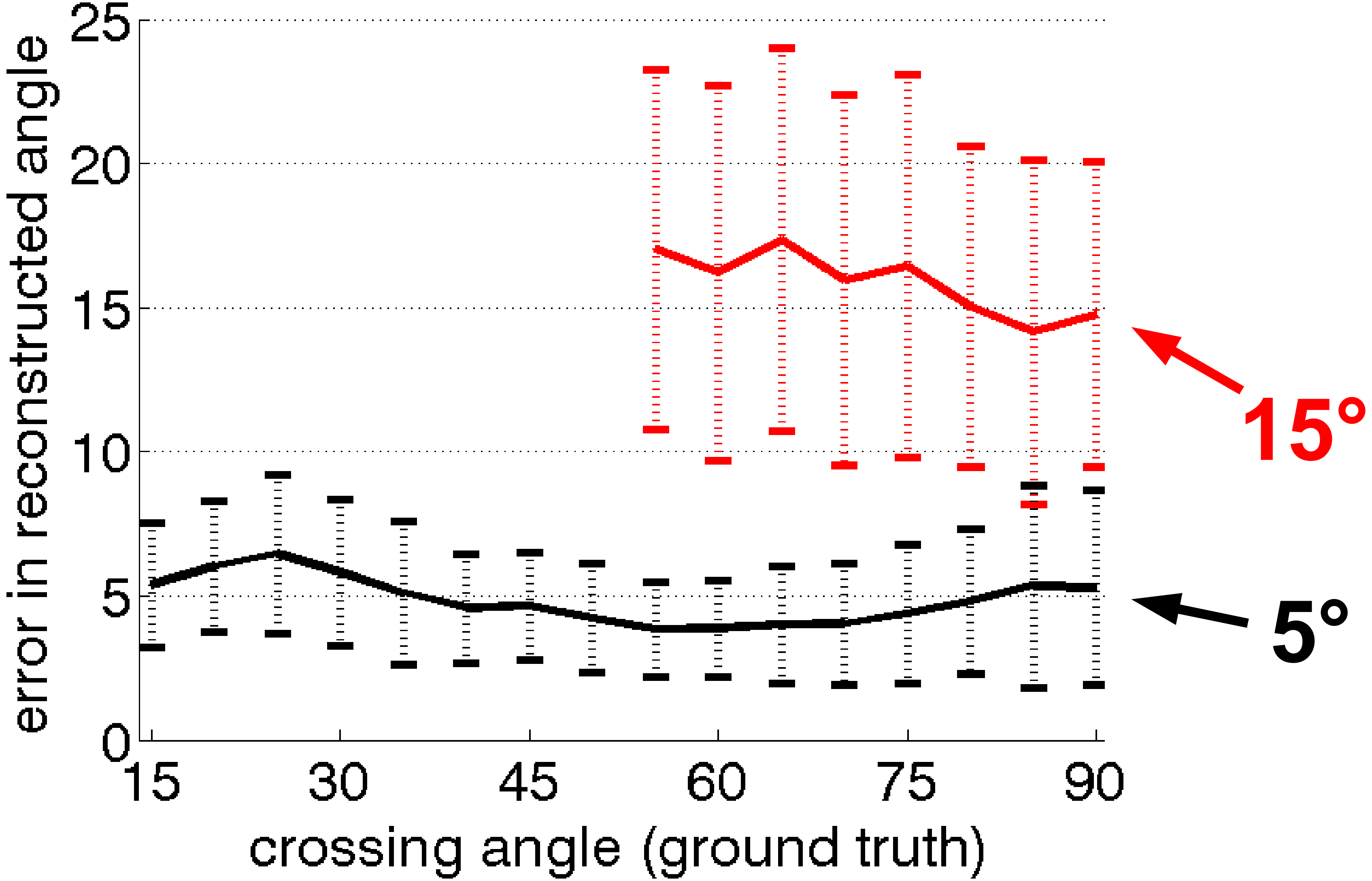
SNR ≈ 5, b = 1000

angular reconstruction error

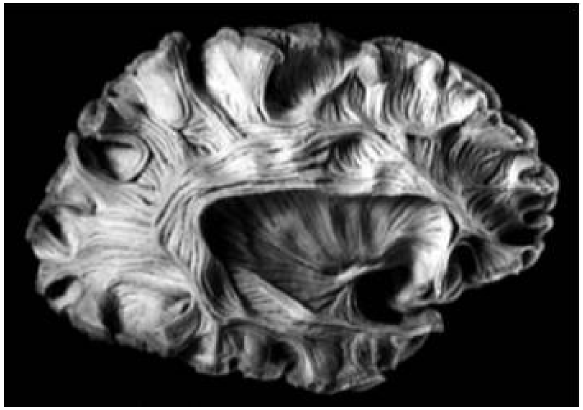


SNR ≈ 5, b = 1000

angular reconstruction error



SNR ≈ 5, b = 1000



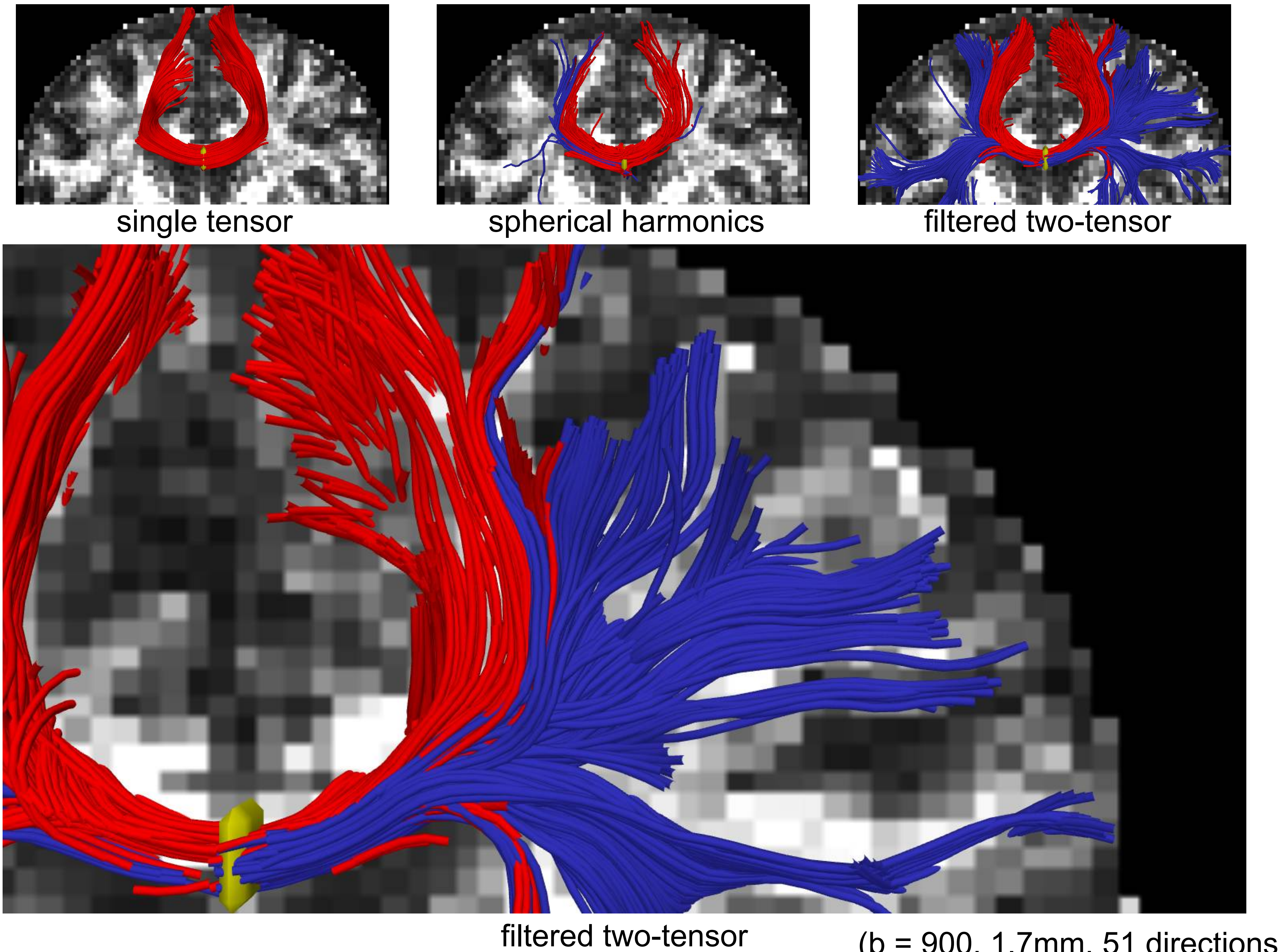
in vivo

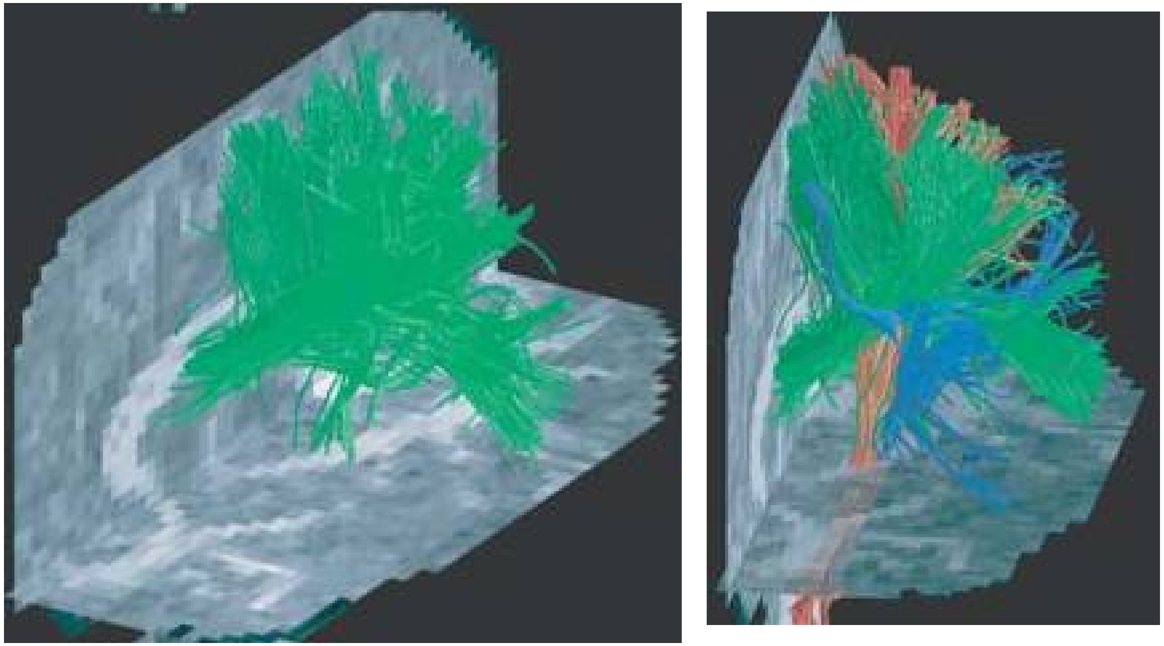
b=900
51 directions
1.7mm isotropic voxel
17 minute scan

algorithm

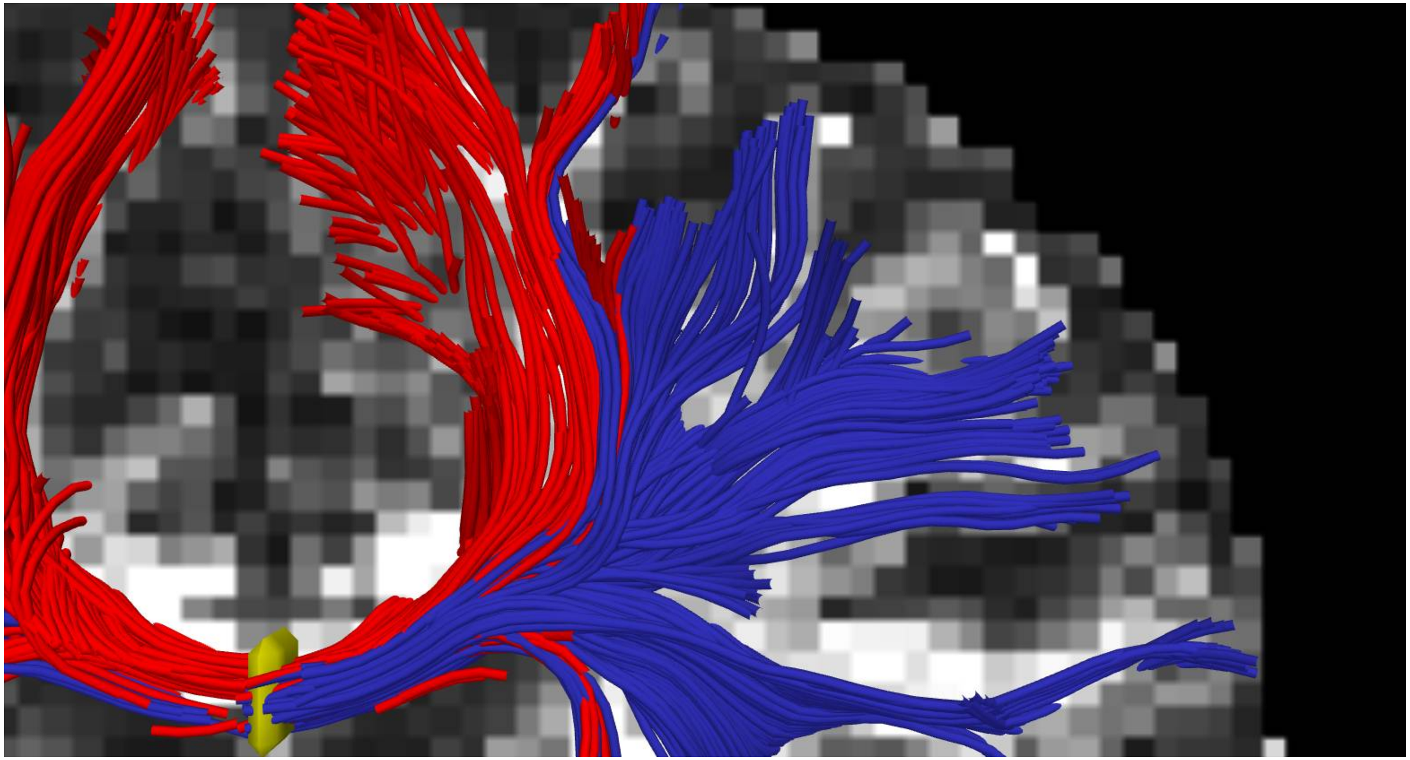
1) interpolate scanner signal (measurement)
2) estimate model parameters with UKF
3) proceed in most consistent direction
4) repeat

- branch: $\theta < 40^\circ$
- terminate: $FA < 0.15$ or $GA < 0.10$

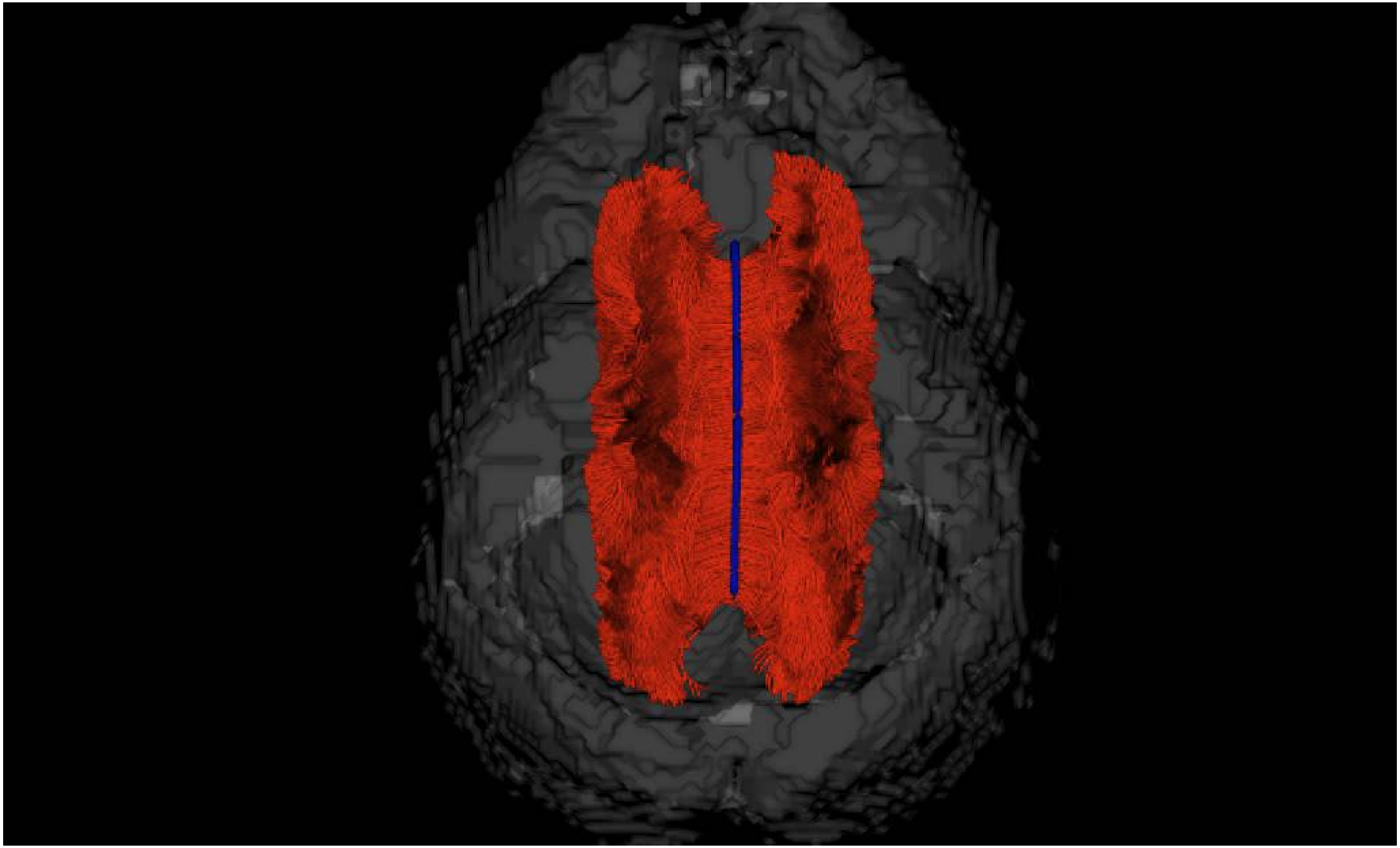

single tensor
spherical harmonics
filtered two-tensor
filtered two-tensor
(b = 900, 1.7mm, 51 directions)

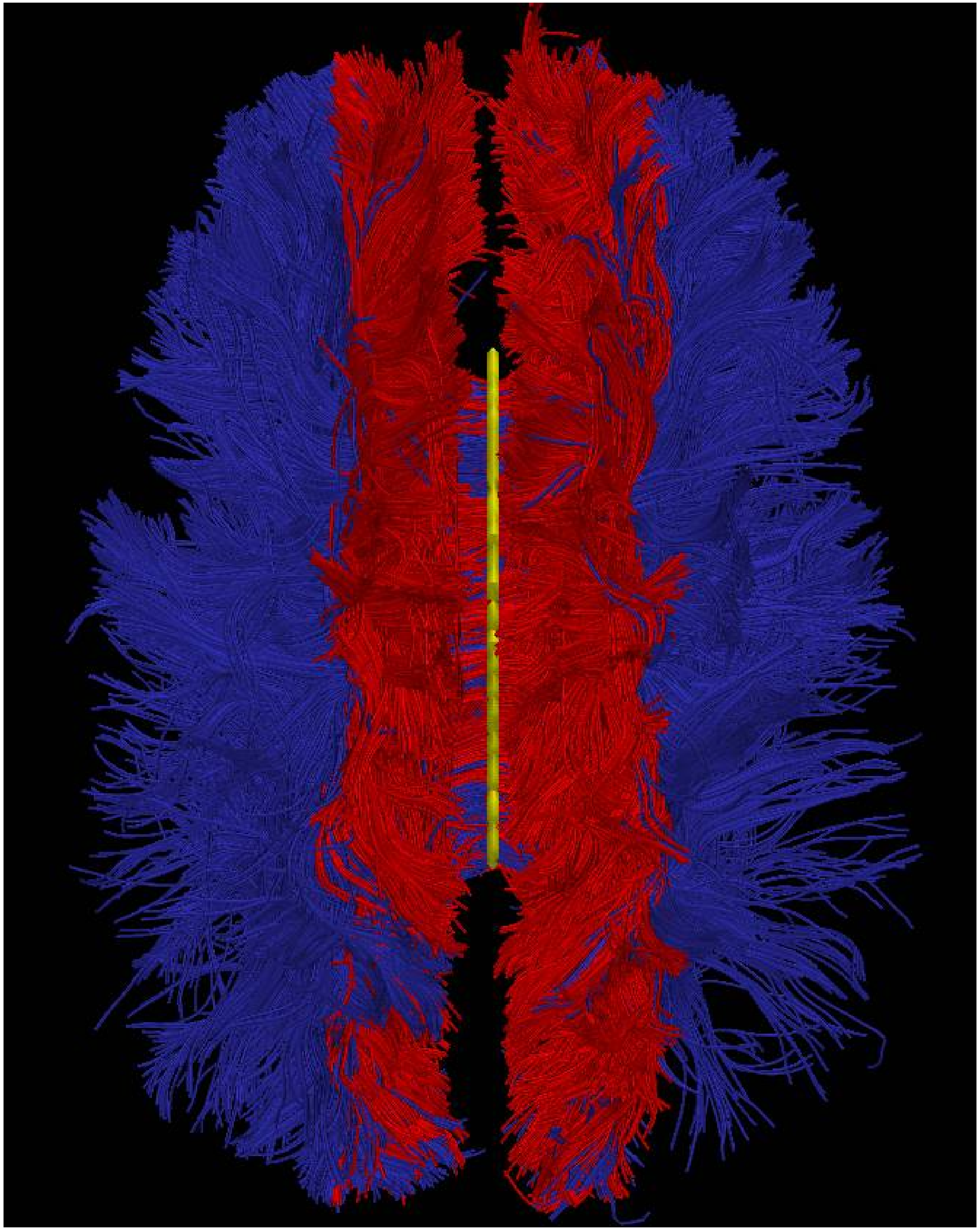


DSI [Hagmann 05]



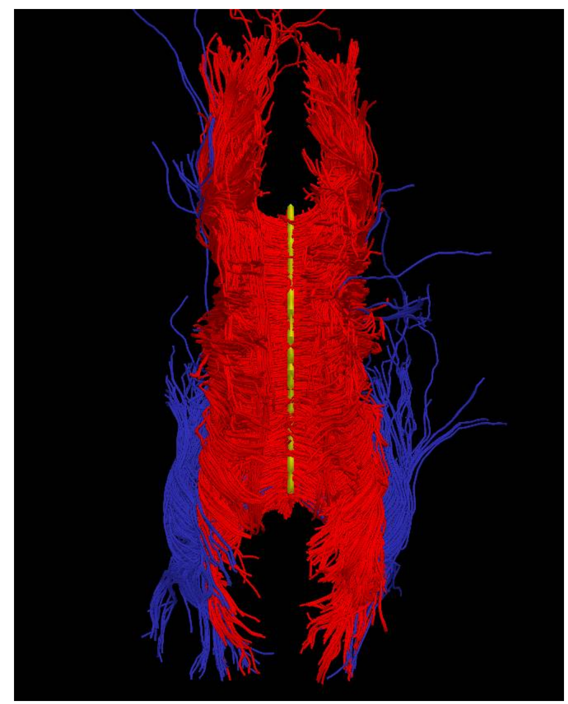
filtered two-tensor



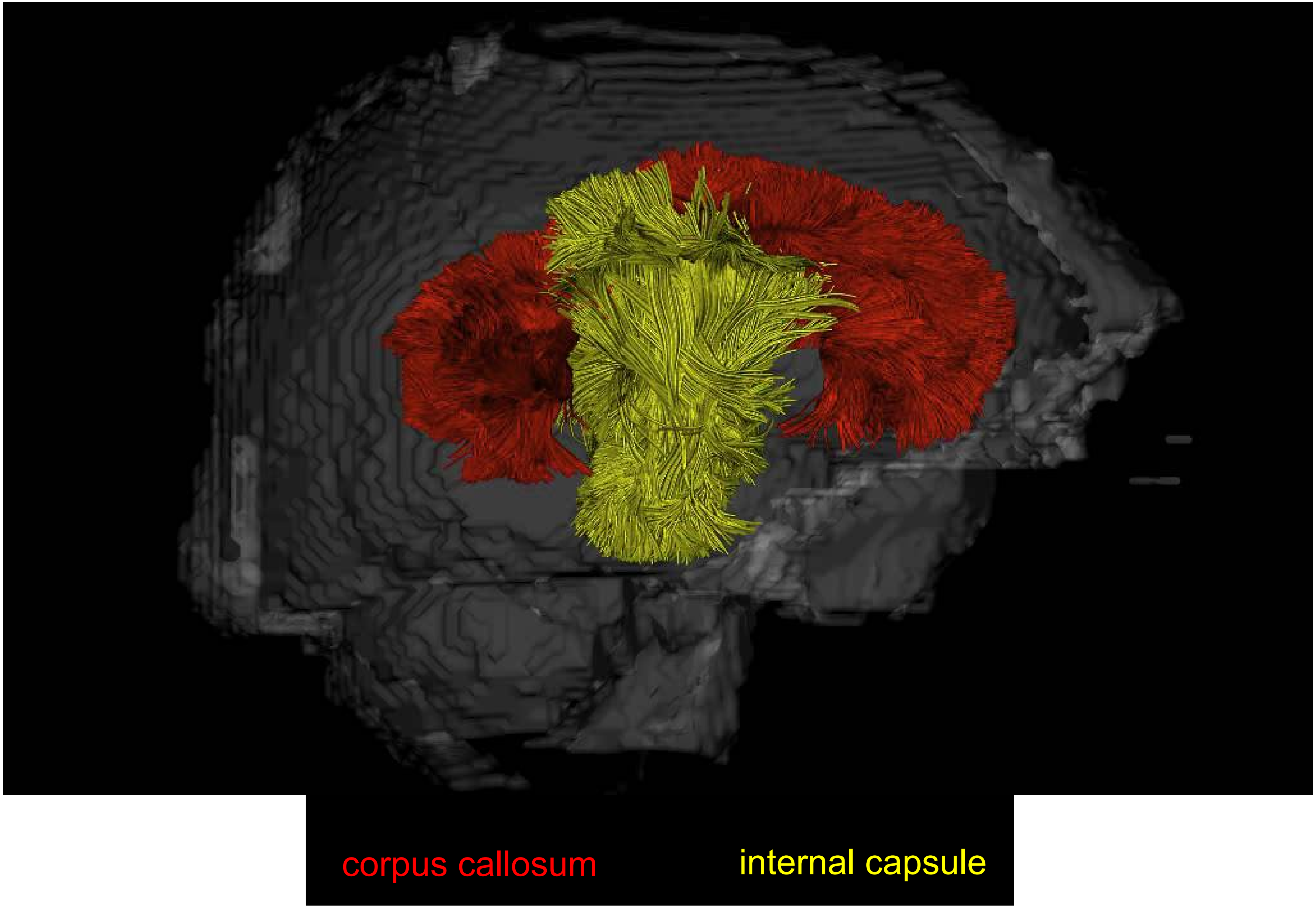


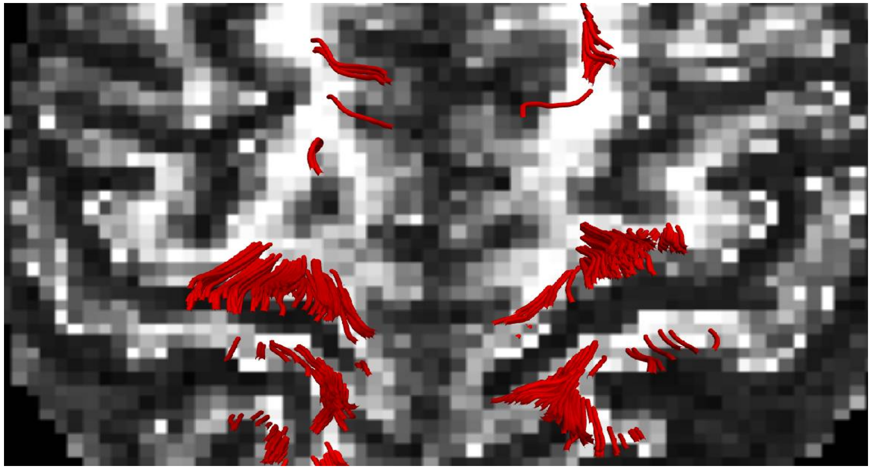
filtered two-tensor

single tensor

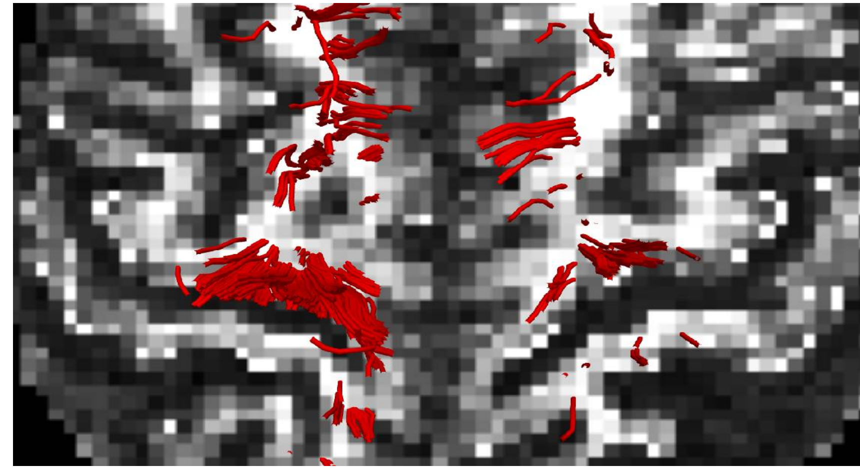


spherical harmonics

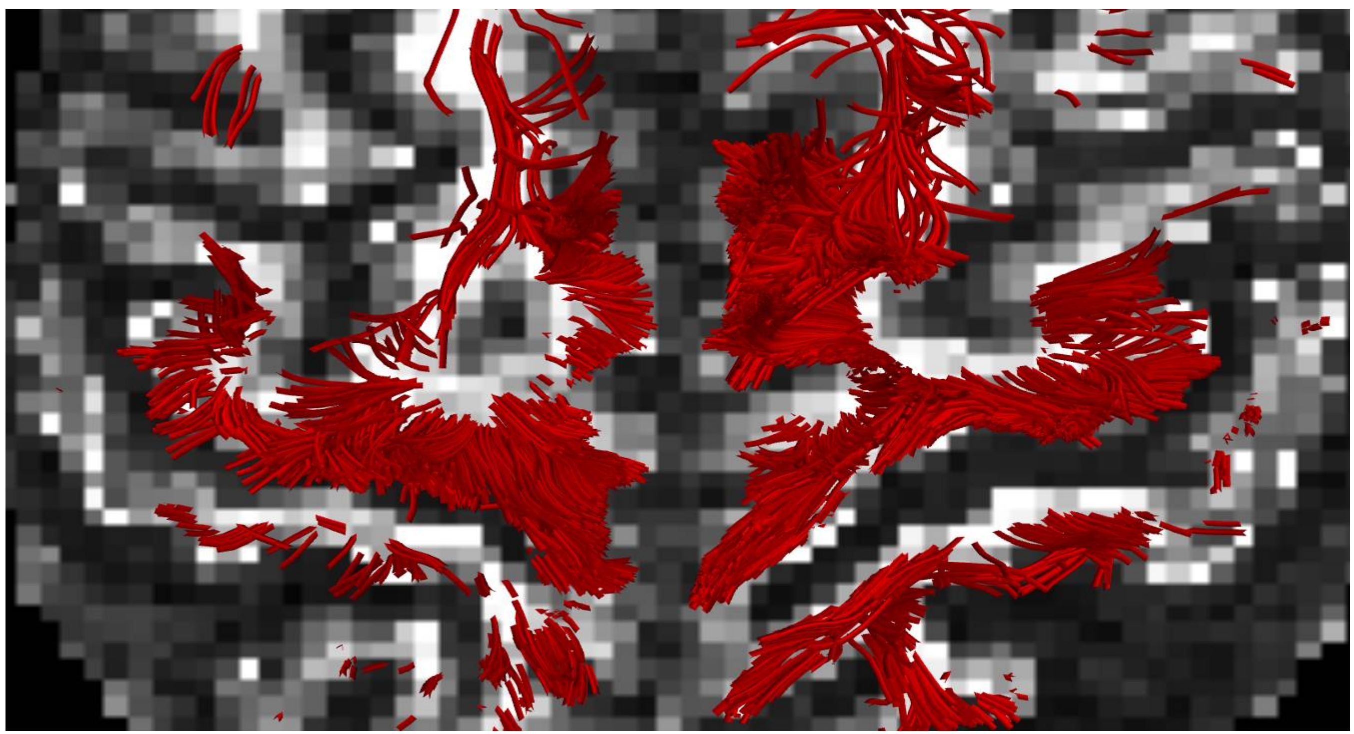

corpus callosum
internal capsule



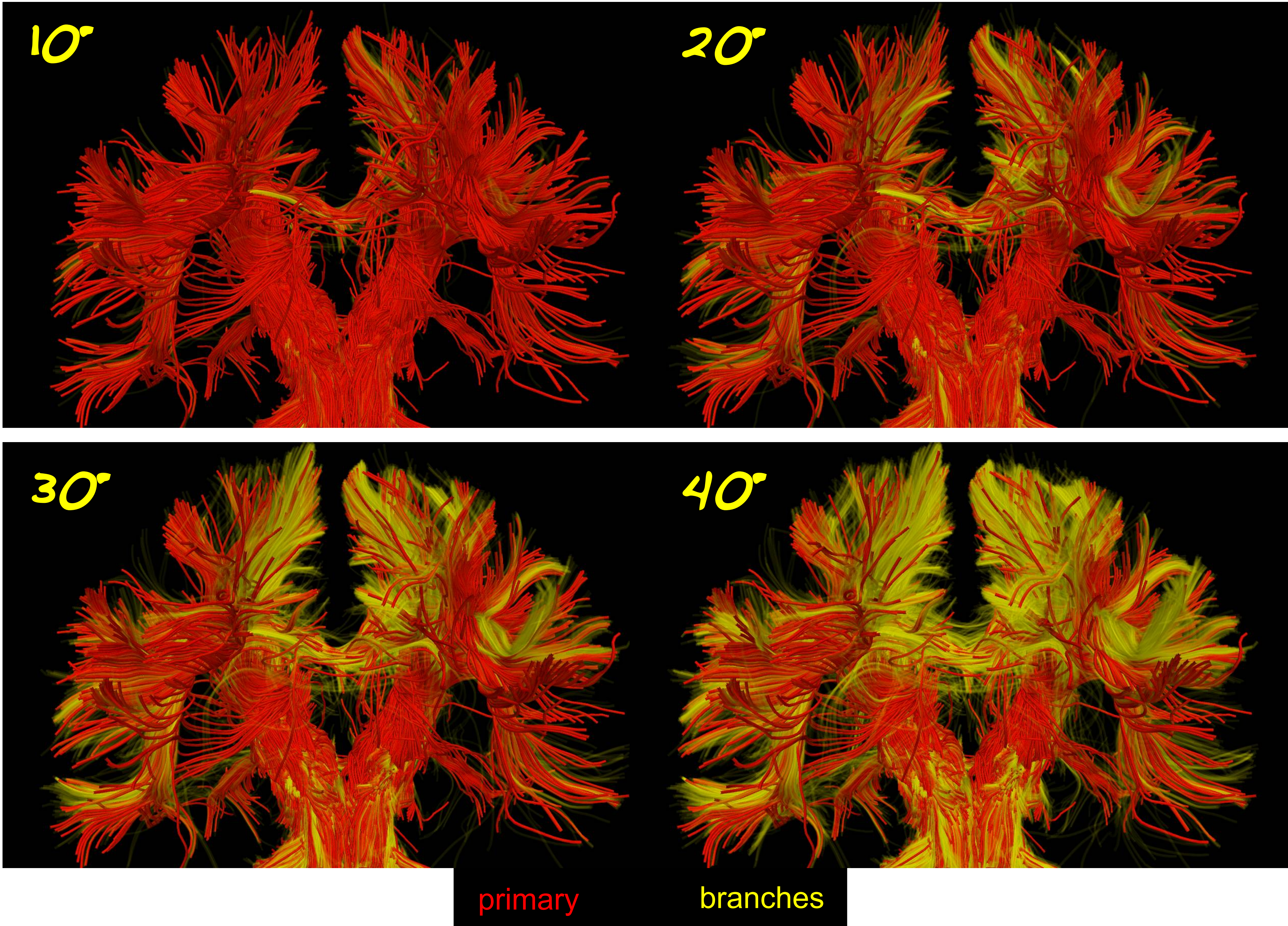
single tensor



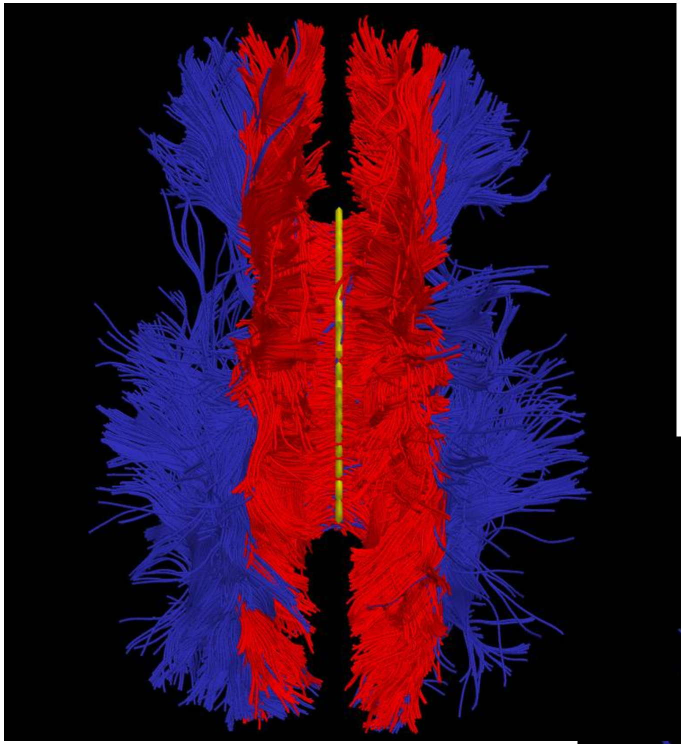
spherical harmonics



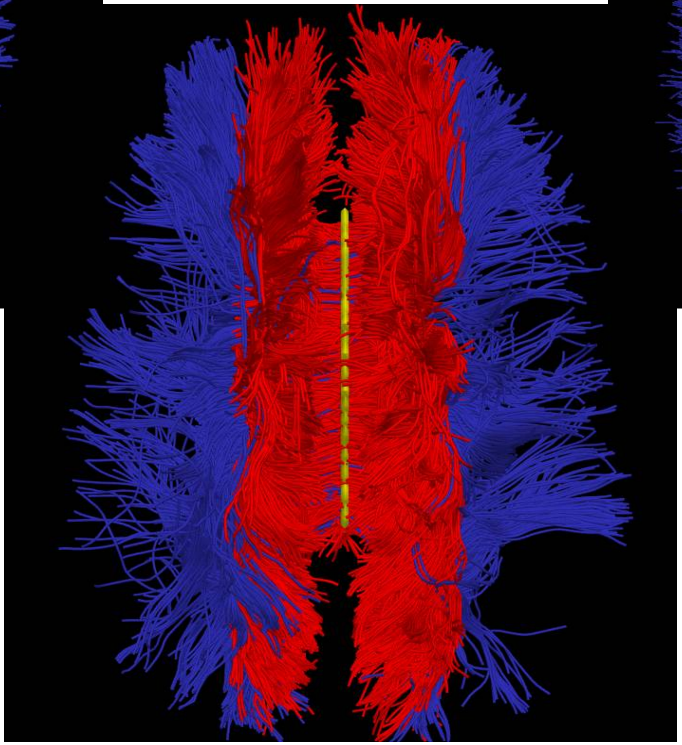
filtered two-tensor


10°
20°
30°
40°
primary
branches

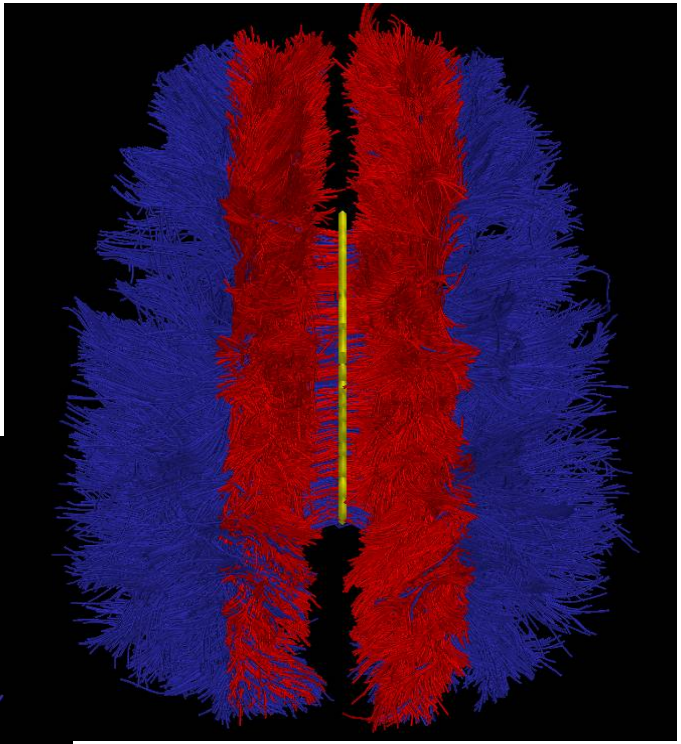
variations on a theme



directional functions



weighted models



three tensors

parametric:
  mixture models
non-parametric:
  spherical harmonics
  higher-order tensors

conclusion

inherent coherence along the fiber

we should exploit it in the estimation

discussion

model assumptions

...in this study

Two fibers

single fiber: align

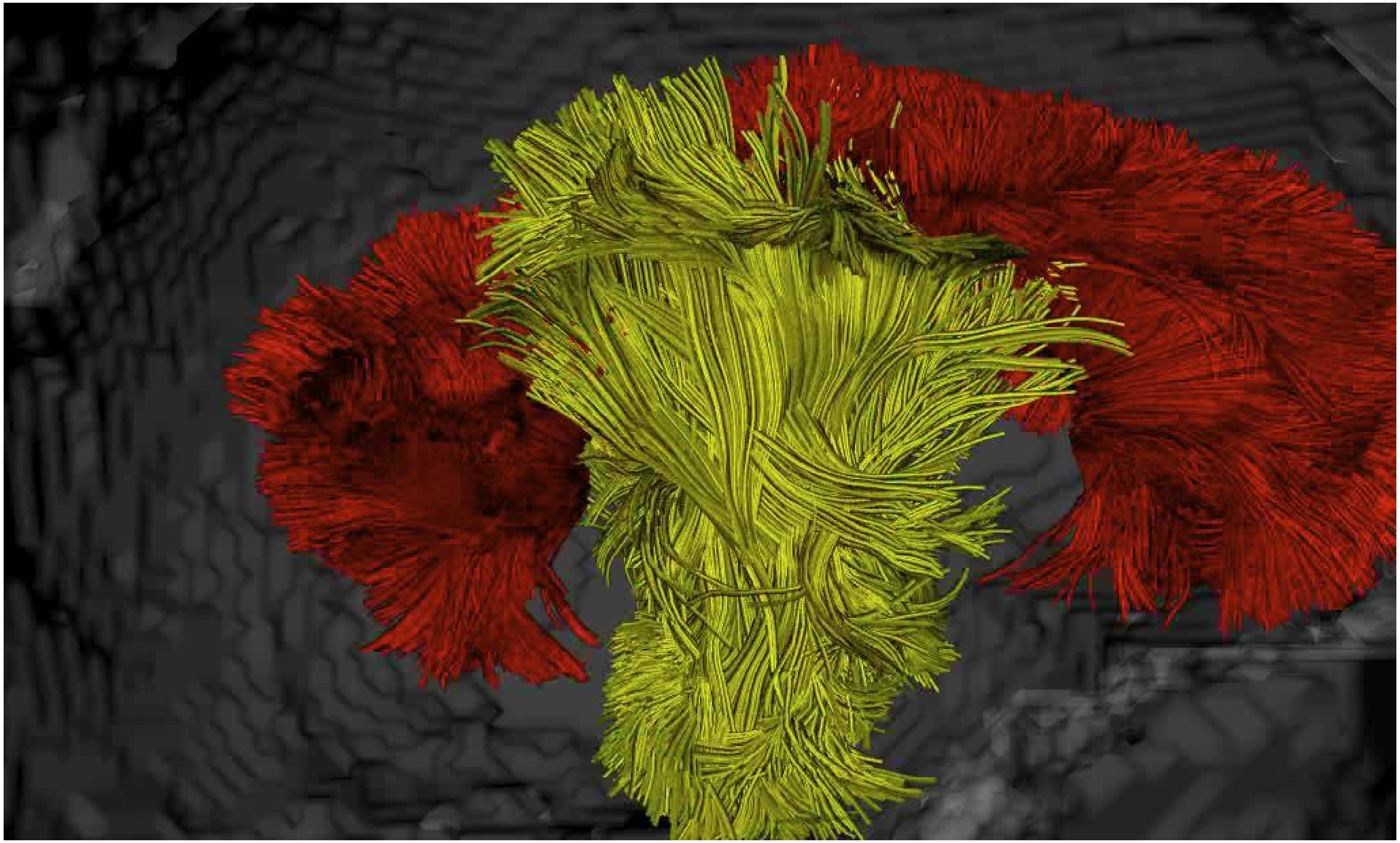
Fixed volume fractions

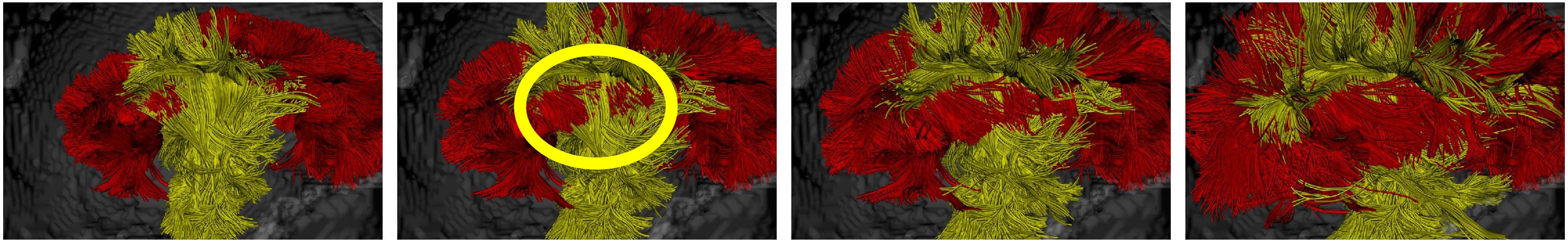
eigenvalues

Tensors are elliptic or isotropic

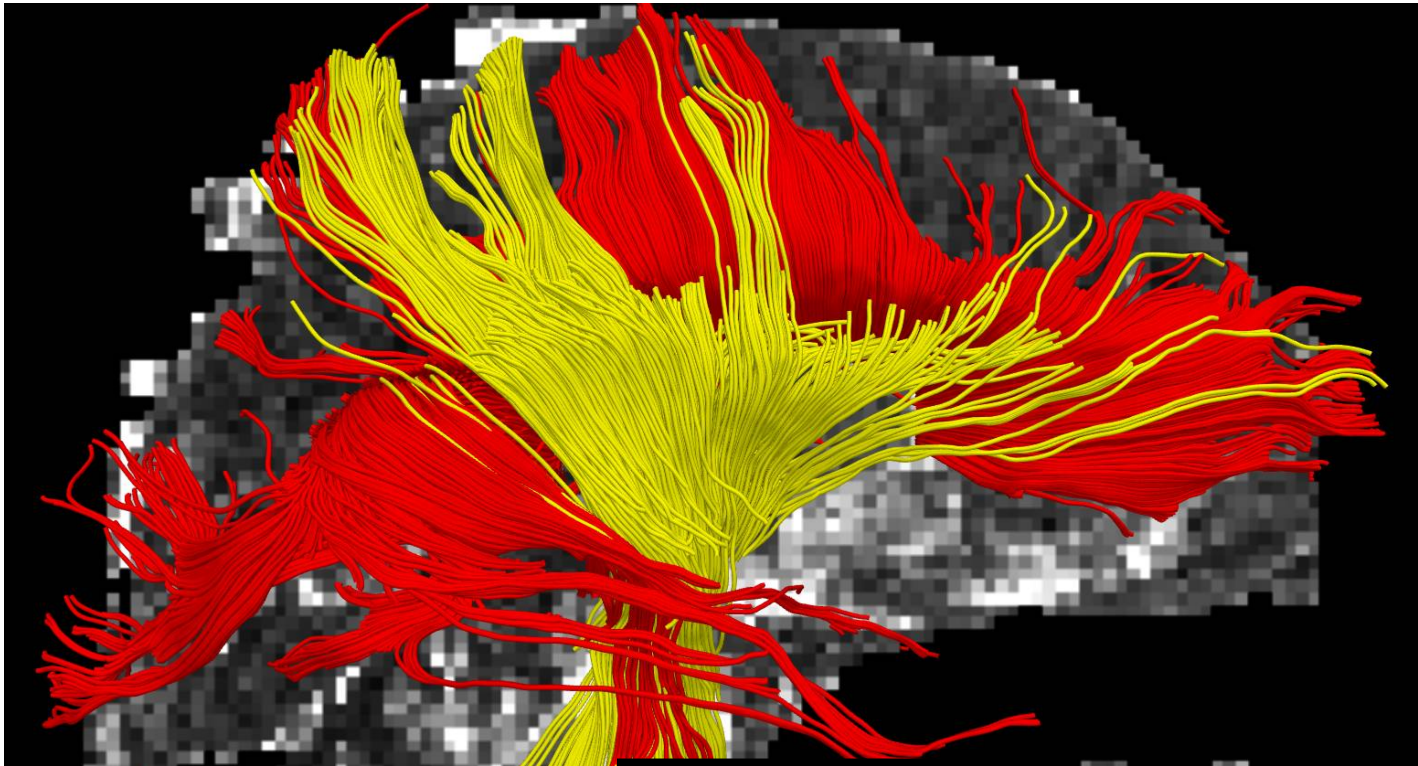
disc ($\lambda_1 = \lambda_2 > \lambda_3$)

model selection, non-parametric, ...



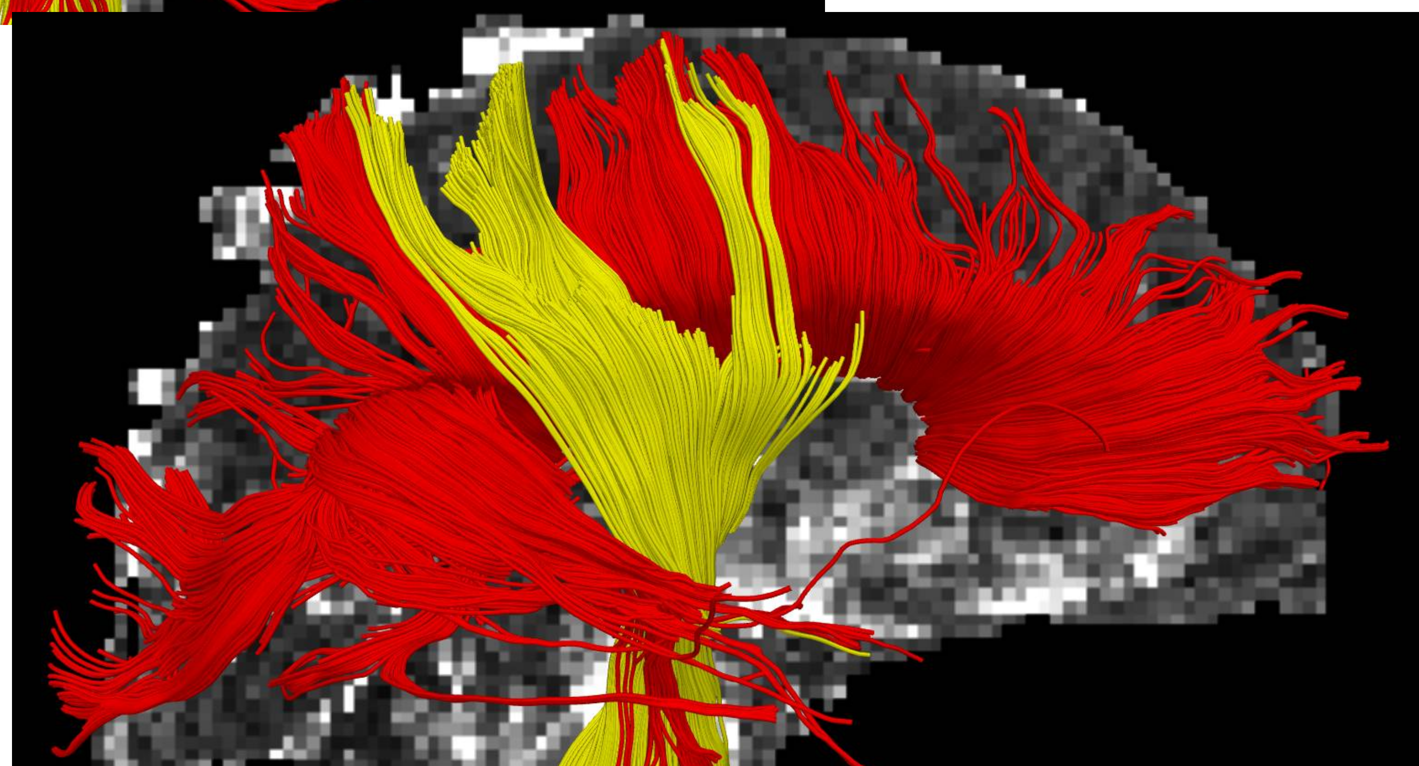


centrum semiovale

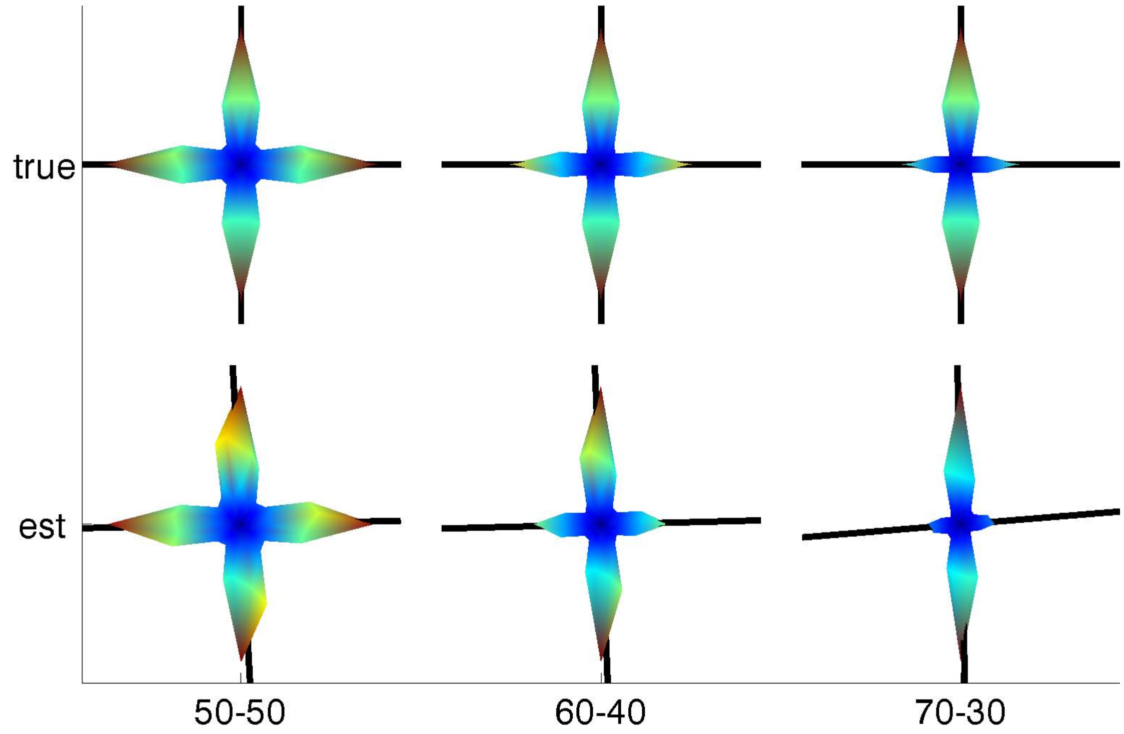


streamline
single-tensor

filtered
single-tensor

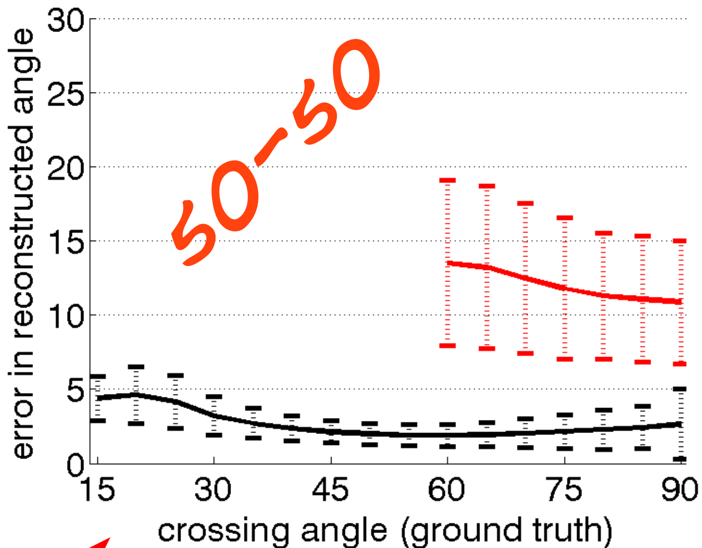


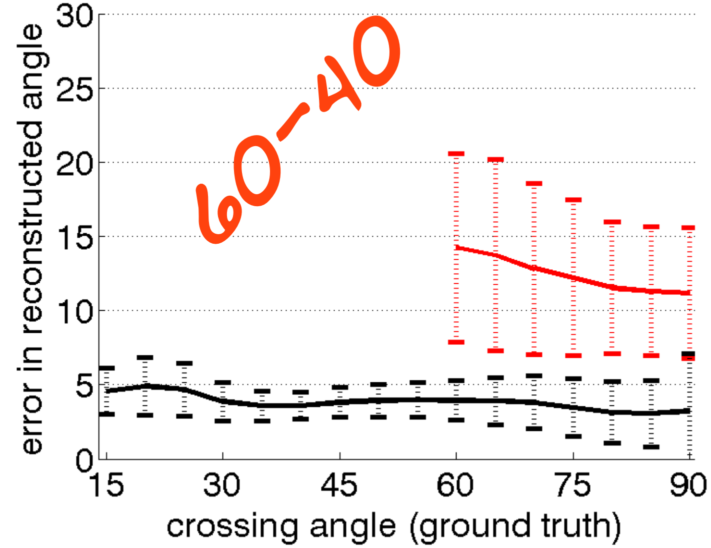
volume fractions



SNR ≈ 10, b = 1000

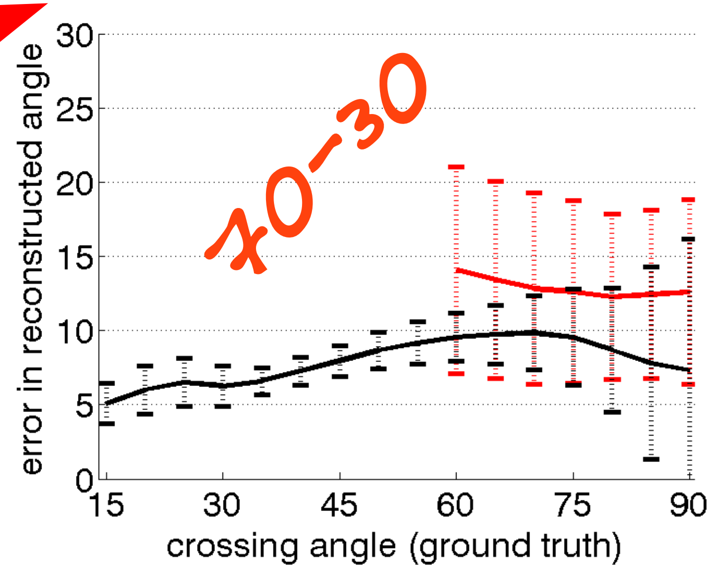
volume fractions





10°

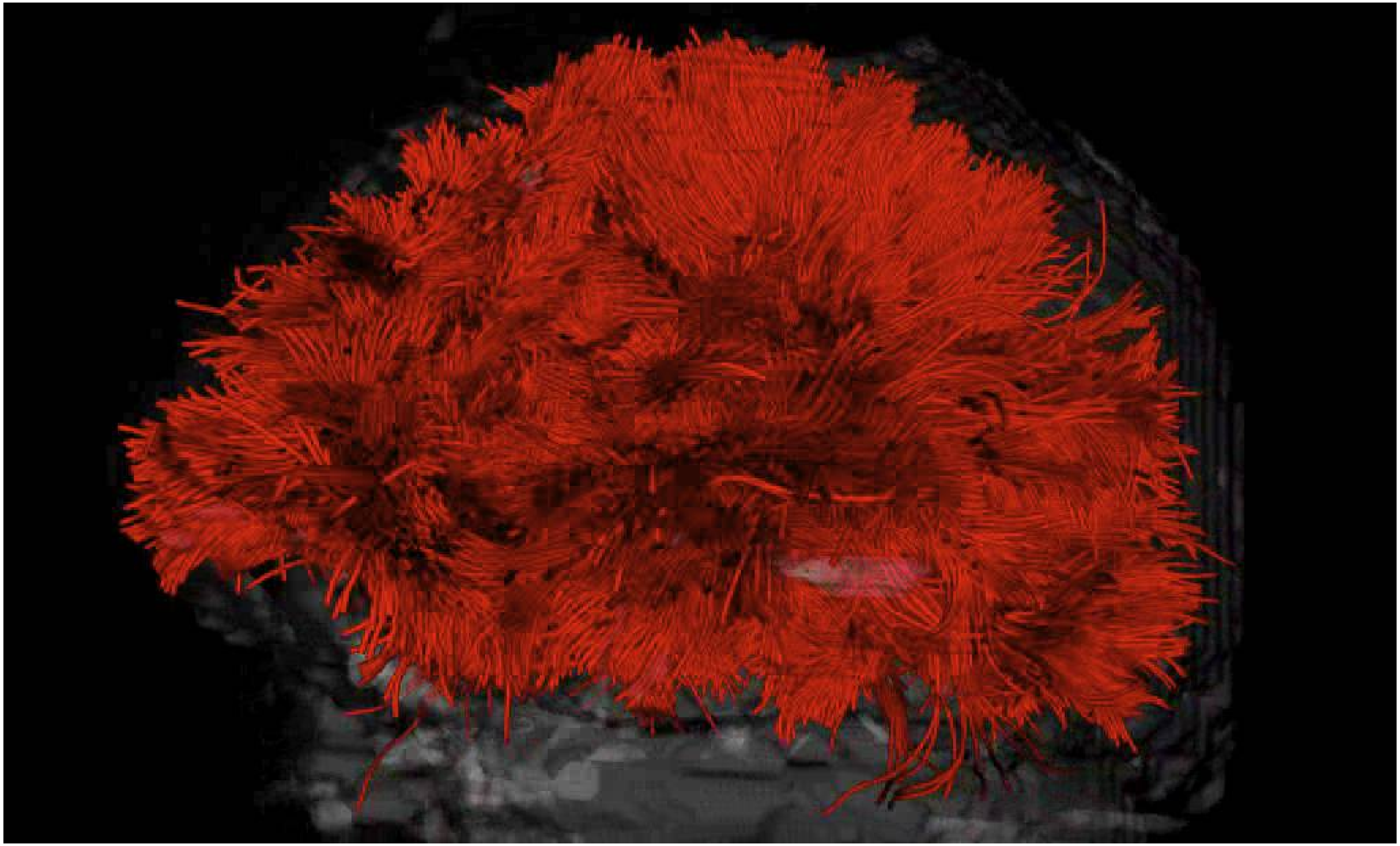
15°



filter deteriorates

SNR ≈ 10, b = 1000

end



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