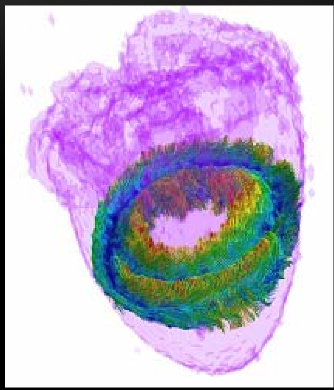
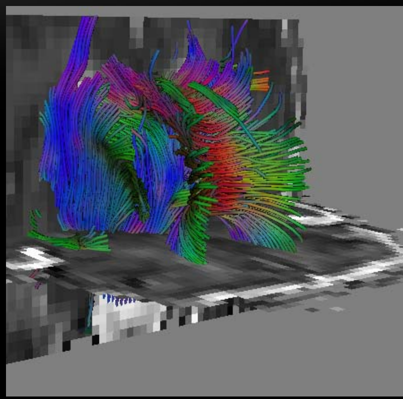
Diffusion Tensor Imaging Visualization Techniques and Applications

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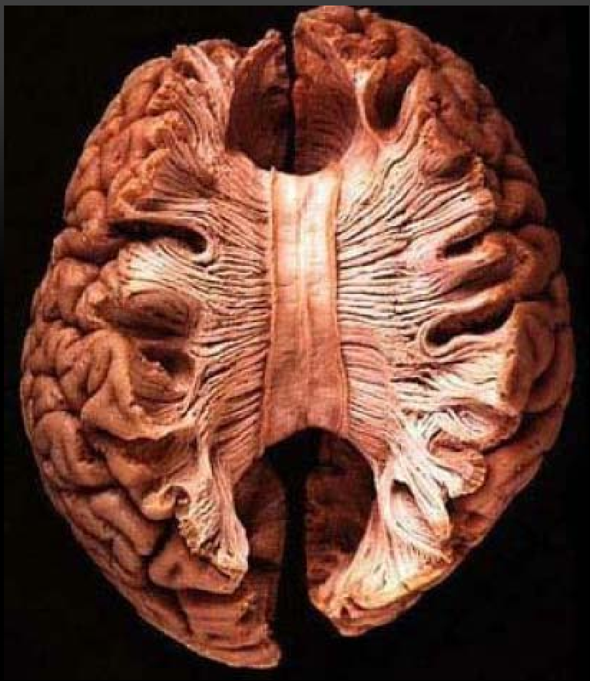
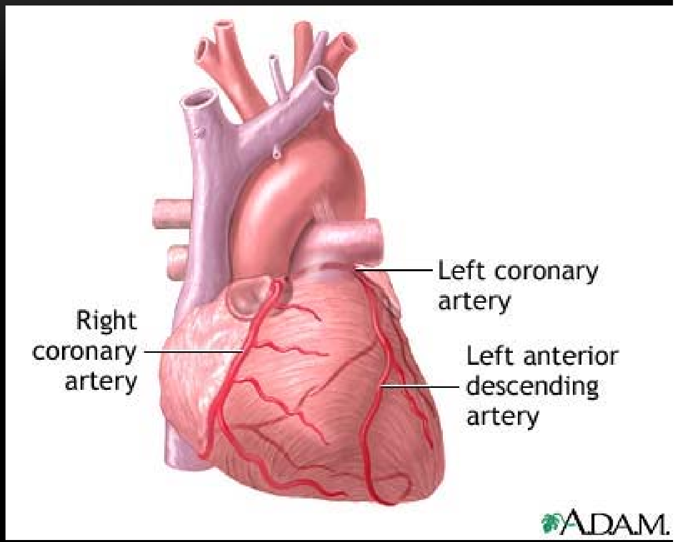
Overview

- Diffusion Tensor Imaging (DTI) data
- DTI visualization techniques
- Applications: newborn and ischemic heart
- Fiber clustering
- DTI segmentation

Motivation



T.H. Williams et al.

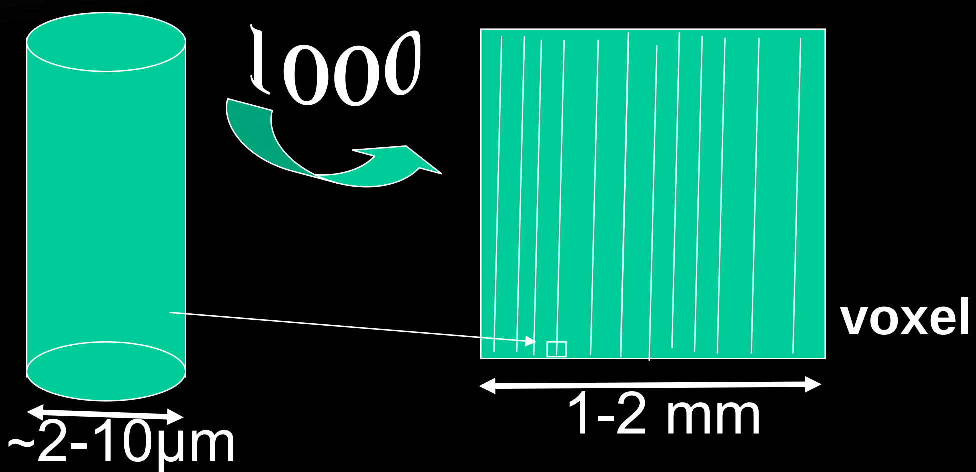


http://www.shands.org/

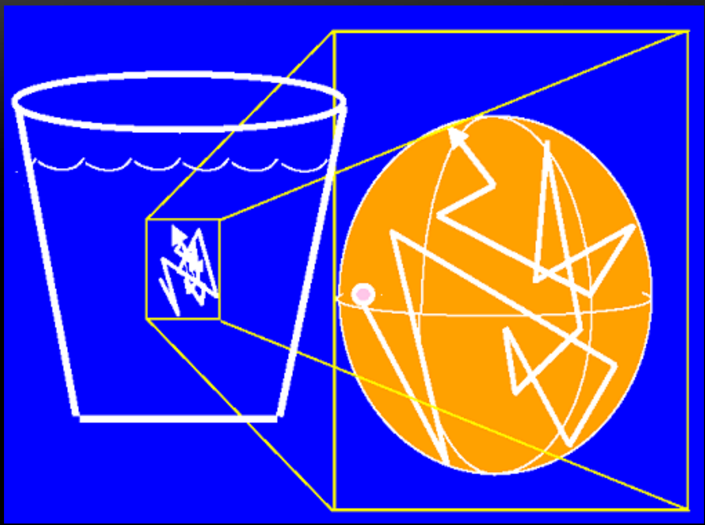
Motivation
MRI and Diffusion Tensor Imaging

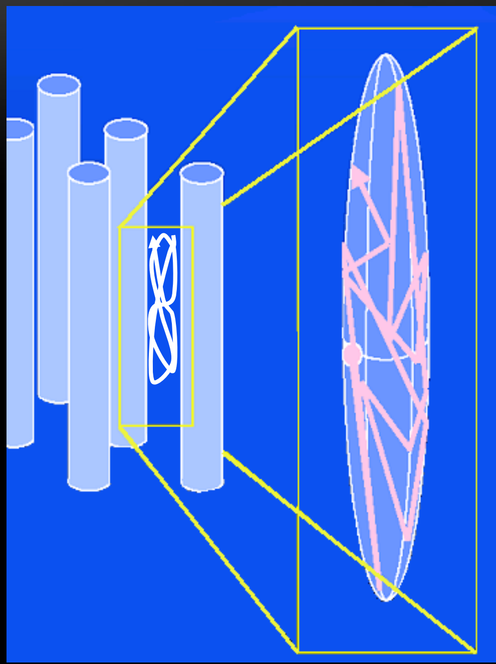
Fibers – Micrometers (~2-10μm)

Scanner (MR) – Millimeters (~1-2 mm)

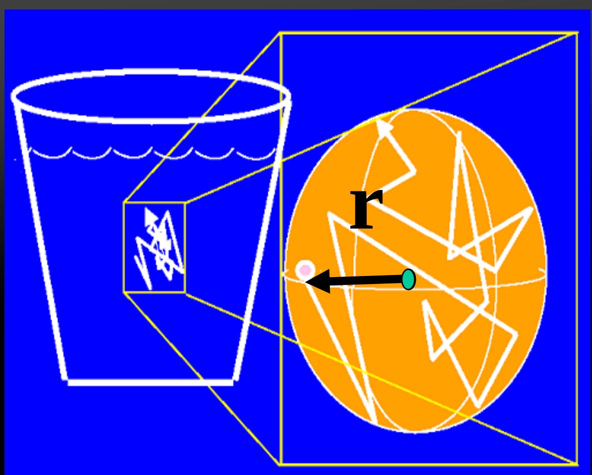


Water Diffusion
Brownian Motion





Fick's Law



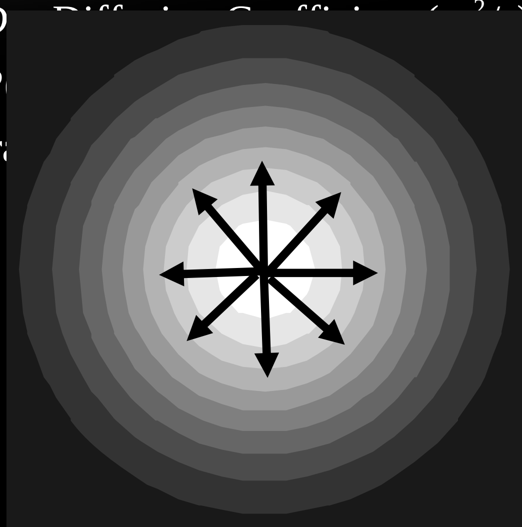
$$\frac{\partial}{\partial t}P(\mathbf{r},t) = D \cdot \nabla^2 P(\mathbf{r},t)$$

t Diffusion time

D Diffusion Coefficient (m^2/s)

P

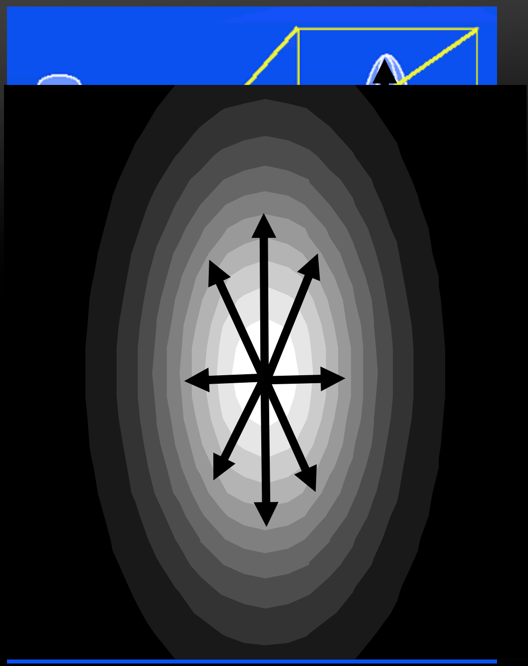
tr



Solution -3D Gaussian

$$P(\mathbf{r},t) = \frac{1}{(4\pi D t)^{3/2}} e^{-\frac{1}{4t}\mathbf{r}^2 D^{-1}}$$

Anisotropic Diffusion



$$P(\mathbf{r},t)=\frac{1}{(4\pi D t)^{3/2}}e^{-\frac{1}{4t}\mathbf{r}^2 D^{-1}}$$

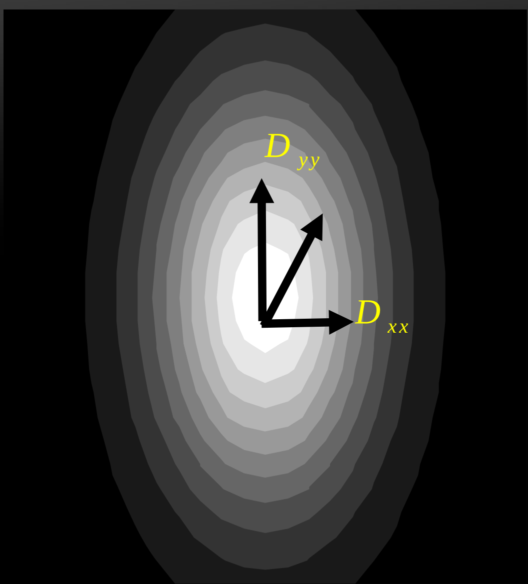
$$P_i(\mathbf{r}_i,t)=\frac{1}{(4\pi D_i t)^{3/2}}e^{-\frac{1}{4t}\mathbf{r}_i^2 D_i^{-1}}$$

Indicates the distance squared of the vector

Anisotropic Diffusion – Diffusion Tensor

Diffusion Tensor

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



$$D_i=\mathbf{r}_i^t\mathbf{D}\mathbf{r}_i$$

$$P(\mathbf{r},t)=\frac{1}{(4\pi|\mathbf{D}|t)^{3/2}}e^{-\frac{1}{4t}\mathbf{r}^t\mathbf{D}^{-1}\mathbf{r}}$$

MR measurements

VIS08 VIS • INFOVIS • VAST

- Measure Diffusion Weighted signal S_i in a given direction
- Stejskal-Tanner relationship attenuation signal S_i to diffusion coefficient D_i

$$S_i = S_0 e^{-bD_i}$$

where S_0 not diffusion weighted value
b protocol parameter (diffusion time, ...)

is often called ADC_i (Apparent Diffusion Coefficient) – D_i diffusion in a given direction

MRI-Diffusion Measurement

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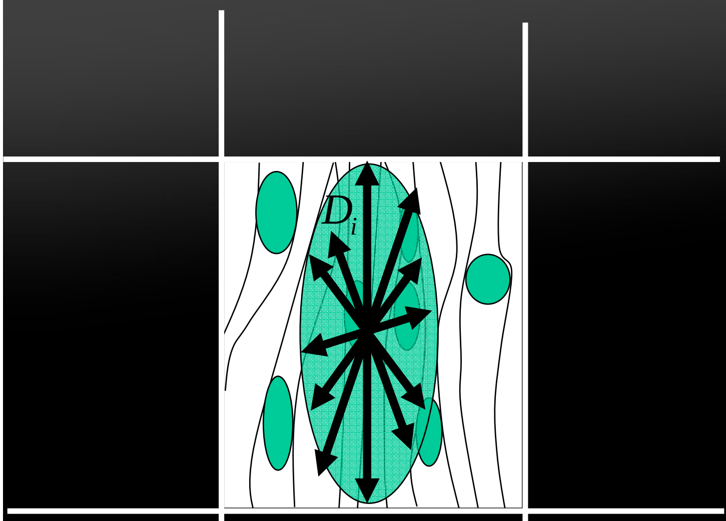


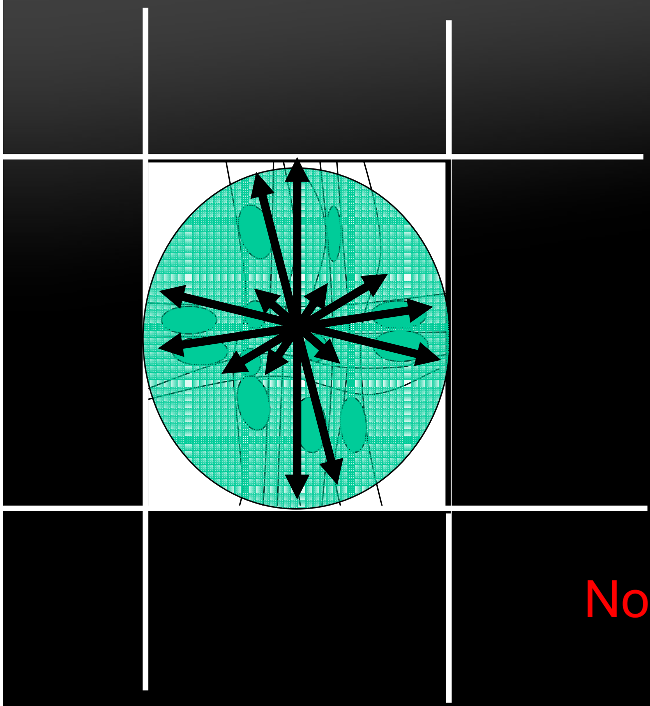
Axis indicates preferred direction

Measure ADC_i in a lot of directions (Minimum 6)

Fit **D**
2nd Order Tensor
Symmetric
Positive Definite

Assume Gaussian
within a voxel

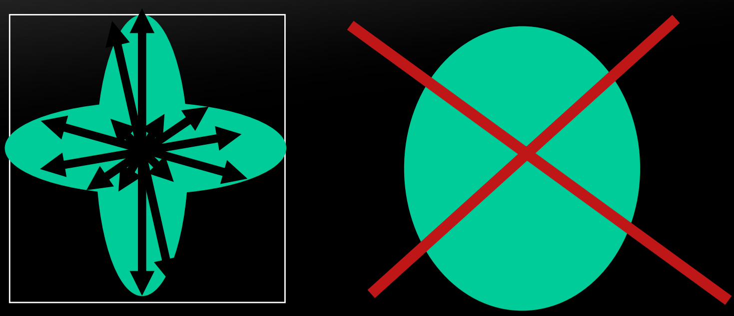
What problems does the Gaussian model have?



No preferred diffusion direction!

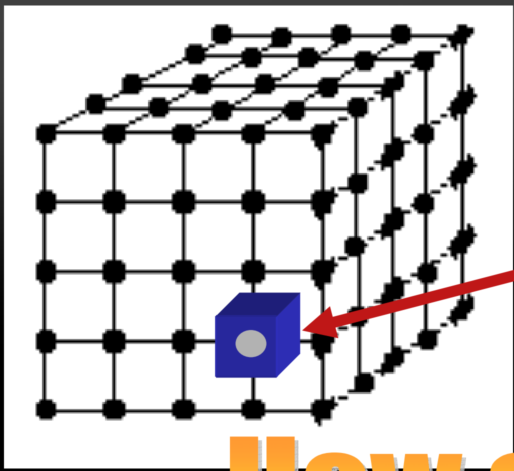
Other models

- HARDI - use other models for the probability density function.



- We will just talk about the Gaussian model!

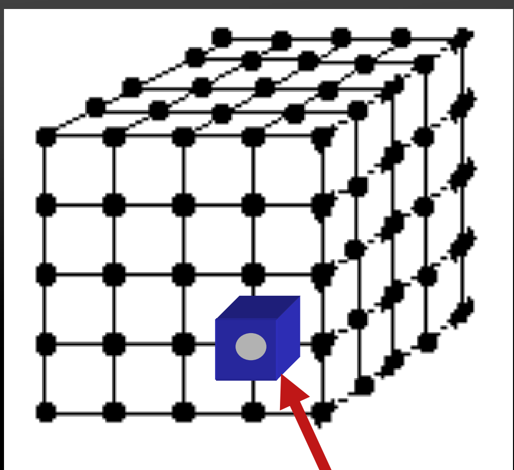
Diffusion Tensor Imaging Visualization

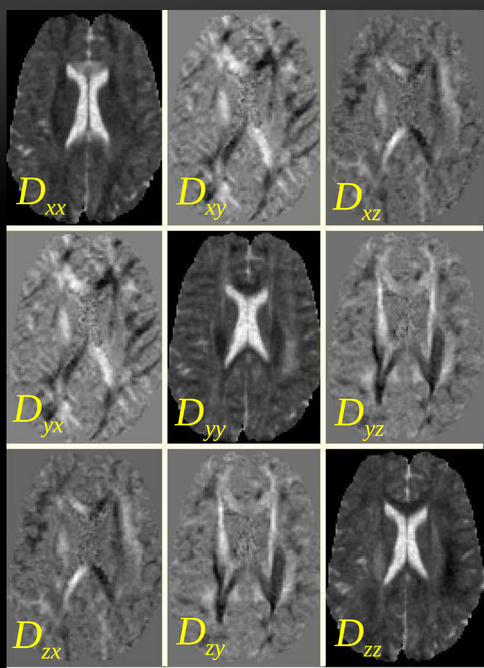


$$\mathbf{D} = \begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{bmatrix}$$

How are we going to show this?

Diffusion Tensor Imaging Visualization



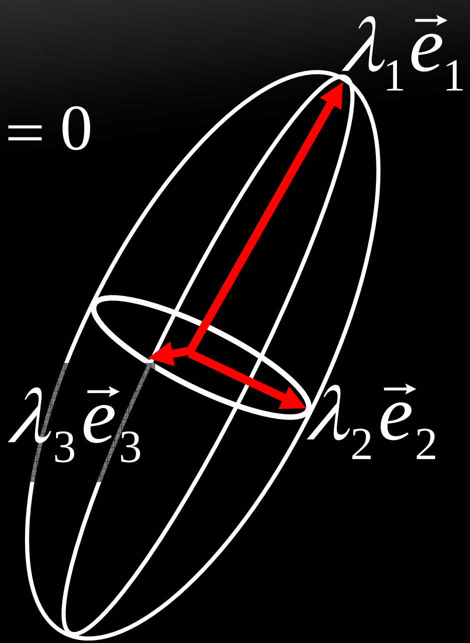


$$\mathbf{D} = \begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{bmatrix}$$

Main diffusion directions

Eigenanalysis

$$\mathbf{D}\vec{e}_i = \lambda_i \vec{e}_i \qquad \det(\lambda \mathbf{I} - \mathbf{D}) = 0$$

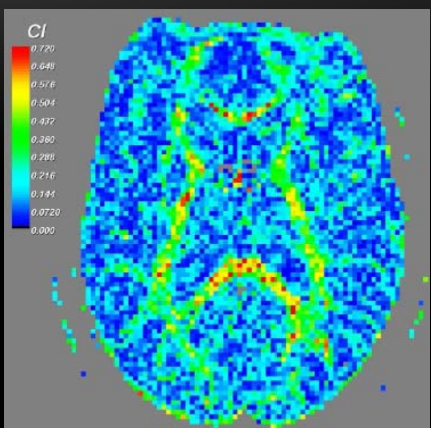


Eigenvalues

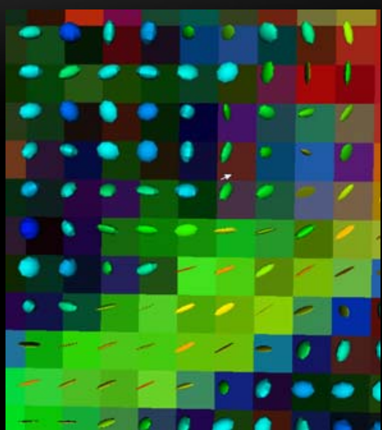
$$\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$$

$$\vec{e}_1, \vec{e}_2, \vec{e}_3$$

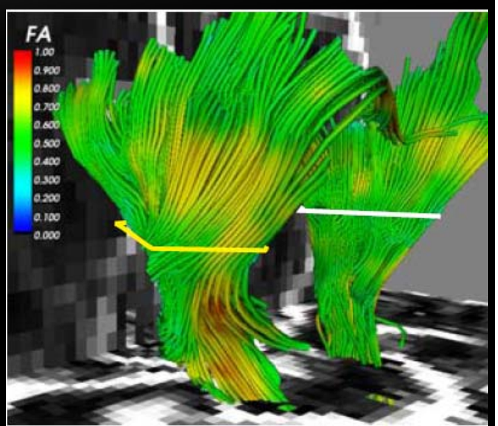
DTI Visualization



Anisotropy Indices



Glyphs



Fiber Tracking

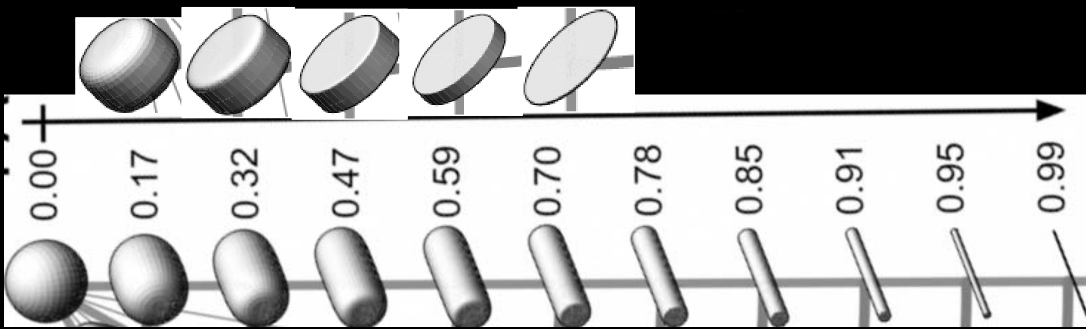
Anisotropy indices

Index that indicates anisotropy

- Fractional Anisotropy

$$FA = \frac{\sqrt{2}}{2}\sqrt{\frac{(\lambda_1-\lambda_2)^2+(\lambda_2-\lambda_3)^2+(\lambda_1-\lambda_3)^2}{\lambda_1{}^2+\lambda_2{}^2+\lambda_3{}^2}}$$

FA



Geometric Diffusion Measures

Isotropy: $\lambda_1 \approx \lambda_2 \approx \lambda_3$

$$C_s = \frac{3\lambda_3}{\lambda_1+\lambda_2+\lambda_3}$$

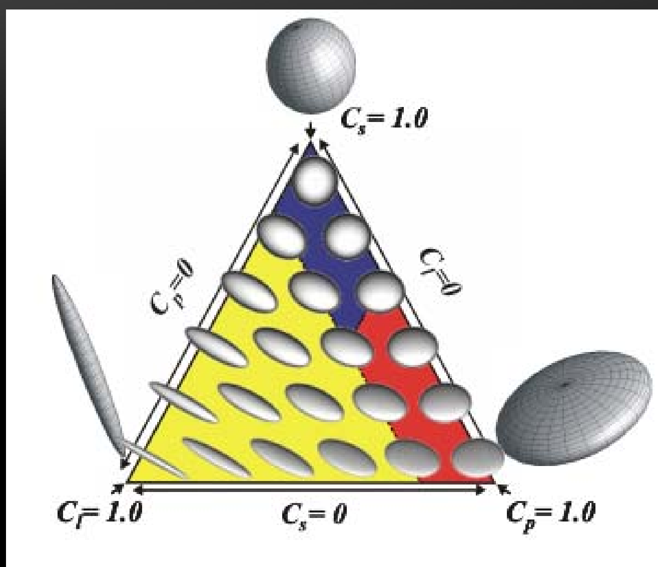
Anisotropy:

Linear $\lambda_1 >> \lambda_2 \approx \lambda_3$

$$C_l = \frac{\lambda_1-\lambda_2}{\lambda_1+\lambda_2+\lambda_3}$$

Planar $\lambda_1 \approx \lambda_2 >> \lambda_3$

$$C_p = \frac{2(\lambda_2-\lambda_3)}{\lambda_1+\lambda_2+\lambda_3}$$



$$C_s + C_l + C_p = 1$$

[Westin et al. 97]

Volume Rendering

Scalar (e.g., Anisotropy index) [Kindlmann et al. 00]

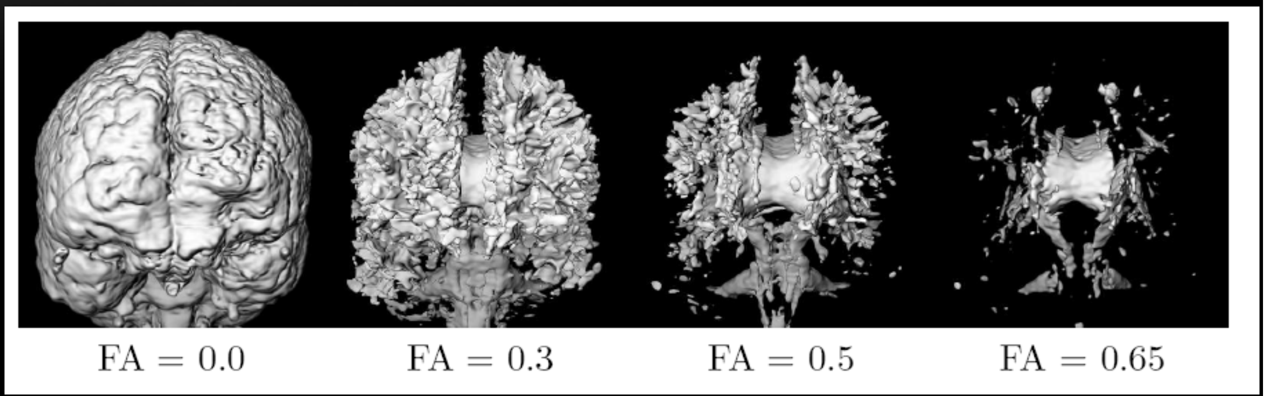


Image from [Vilanova et al. 04]

Anisotropy Indices

There are much more anisotropy indices:

Relative anisotropy (RA), Mean diffusion, etc.

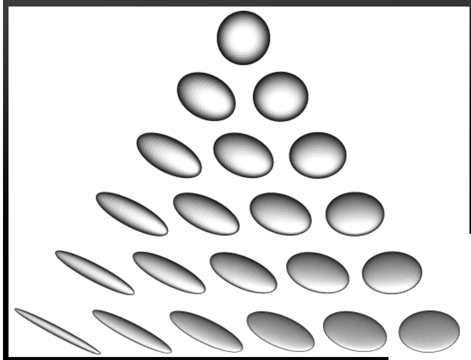
Pros and Cons

- ✓ "Easy" to visualize
- × Simplification 6D → 1D

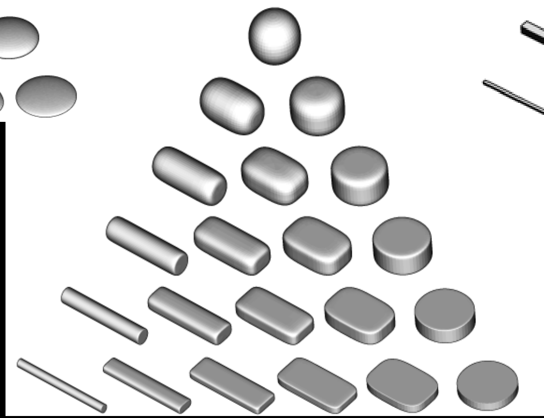
That's a hell of a simplification!

Glyphs/Icons

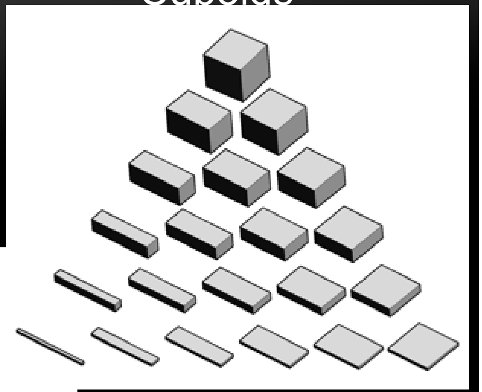
Ellipsoids



Superquadrics



Cuboids



Glyps/Icons

Pros and Cons

- ✓ Shows 6D information
- × Local information
- × Cluttering extended to 3D

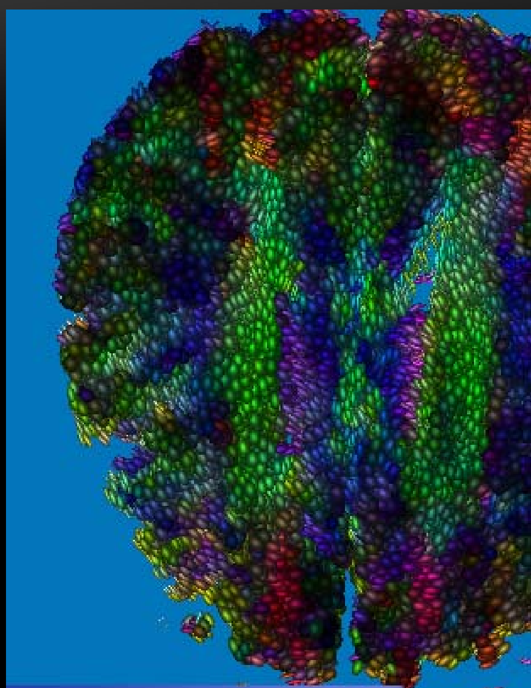


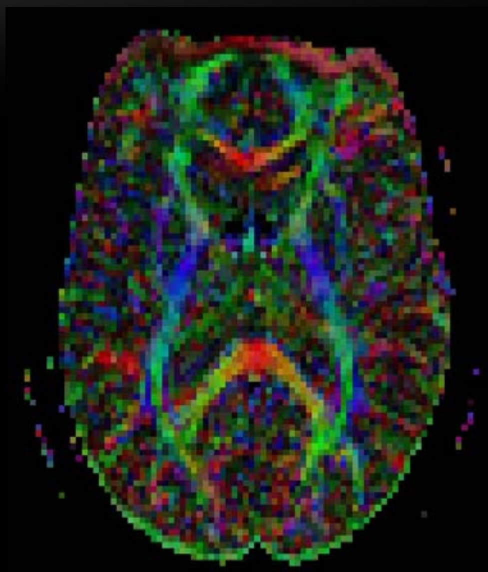
image from [Kondratieva et al. 05]
wwwcg.in.tum.de

Color Coding of the Main Diffusion Direction

$$\vec{e}_1 = (x, y, z) \text{ map to } (R, G, B)$$

Pros and Cons

- ✓ Shows directional information
- ✓ Simple to implement
- × Simplification 6D→3D
- × Difficult to extract fiber information



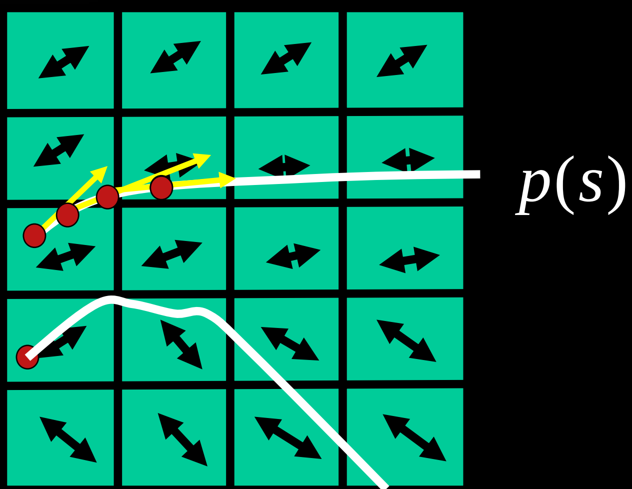
Fiber Tracking
Streamline tracing

Streamline tracing

$$p(s) = \int \vec{e}_1(p(s))ds \qquad p(s) \text{ path with parameter } s$$

Integration scheme

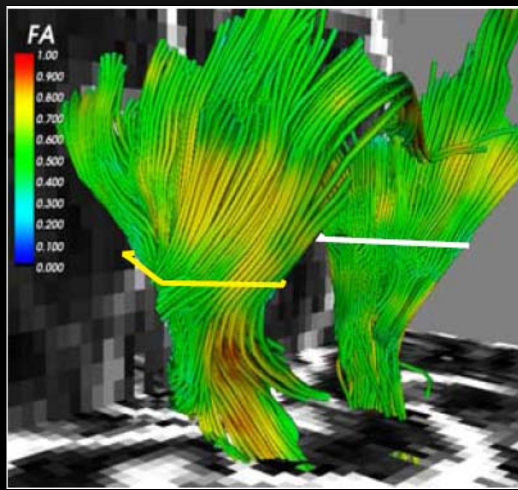
- Euler Forward
- Runge Kutta
- etc.



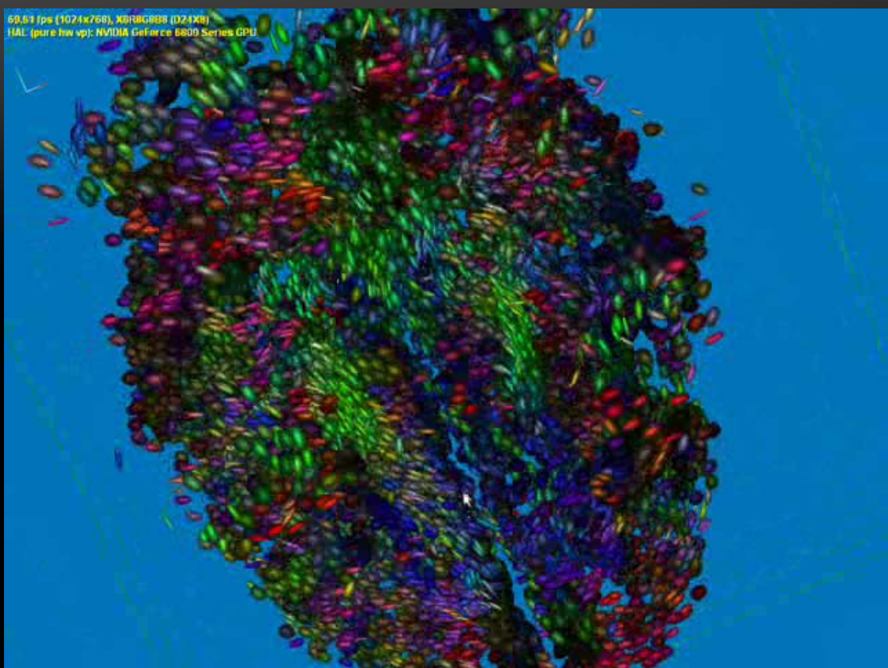
Fiber Tracking
Streamline Tracing

Pros and Cons

- ✓Analogy with fibers
- ✓Shows global information
- ×Simplification 6D → 3D
- ×Problems with Crossing
- ×Seeding – Region of Interest
- ×Cluttering

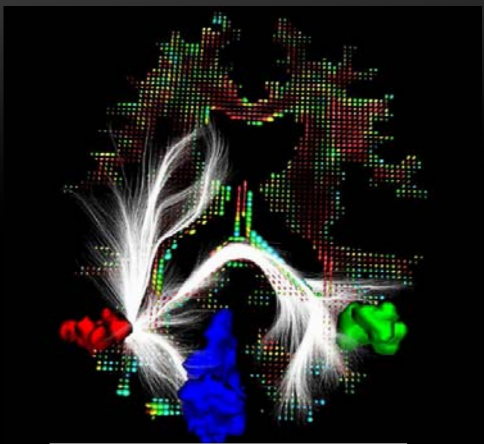


Tracing Glyphs



Video from [Kondratieva et al. 05] wwwcg.in.tum.de

Other Fiber Tracking Techniques

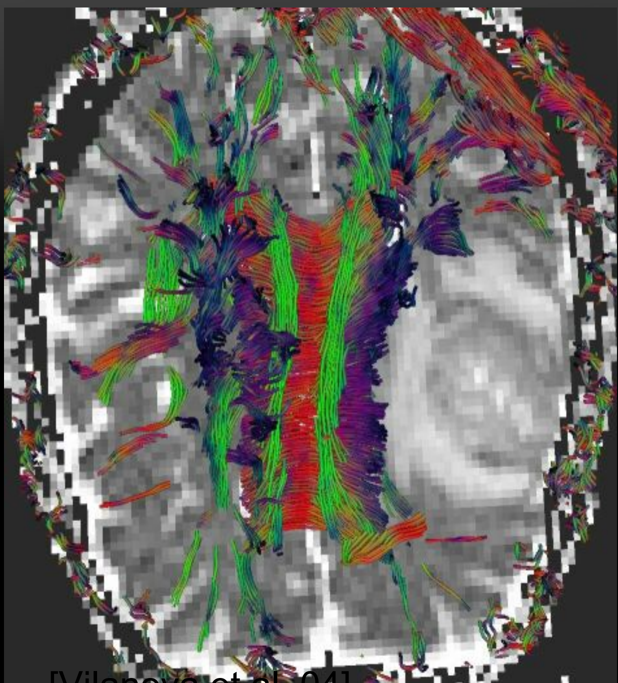


[N.Wotawa et al. 05] 02]

Pros and Cons

- ✓Analogy with fibers
- ✓Shows global information
- ×Seeding – Initial and end
- ×Computational cost
- ×Cluttering

Applications



[Vilanova et al. 04]

Understanding

- Brain Development
- Brain Injuries
- Ischemic heart
- …

Diagnosis

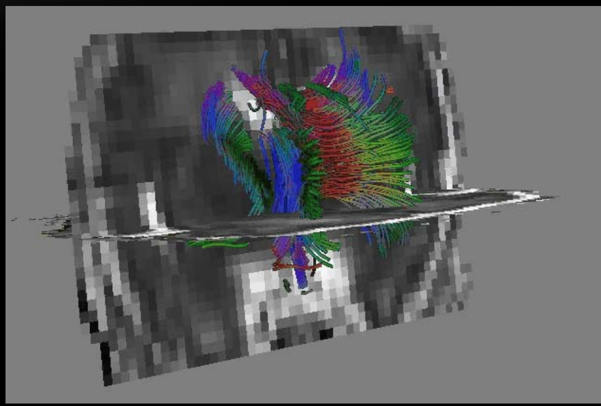
- Epilepsy
- Multiple Sclerosis
- …

Treatment

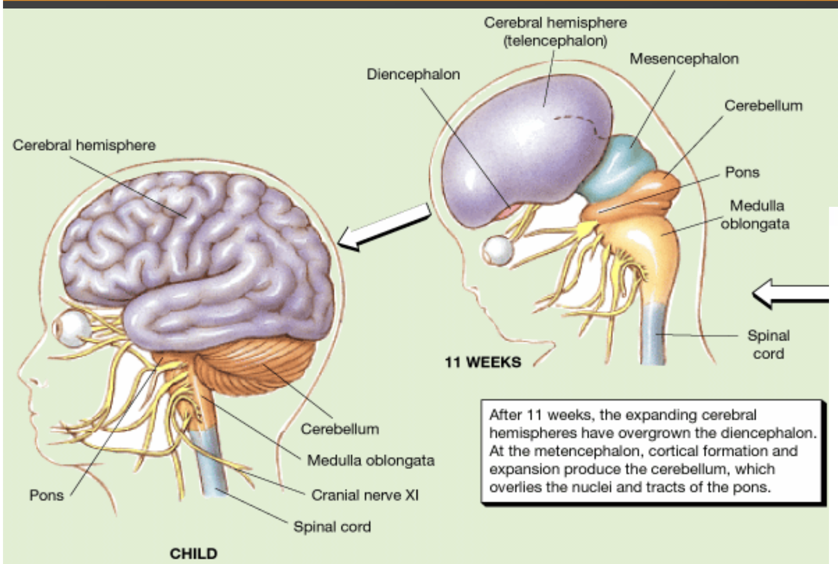
- Tumor resection
- …

DTI in the newborn brain

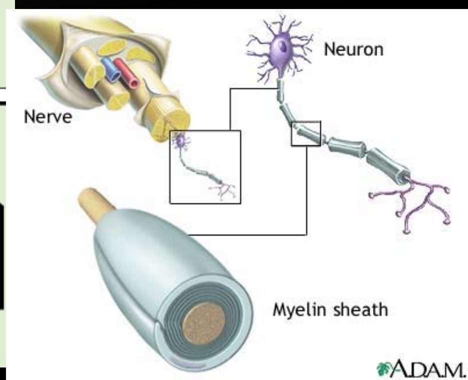
- DTI can reveal detailed anatomy of white matter development.
- Characterization of normal axonal growth of the white matter tracts.
- Understanding the extensive inhomogeneity of white matter injuries (e.g., hypoxic-ischemic regions)
- Reference standards for diagnostic radiology of premature newborns.
- Early detection can improve treatment



Human brain developmentn



Picture from Prentice Hall - cwx.prenticehall.com



Brain myelination starts with 30 weeks of conception and it is not completed until the age 20-30

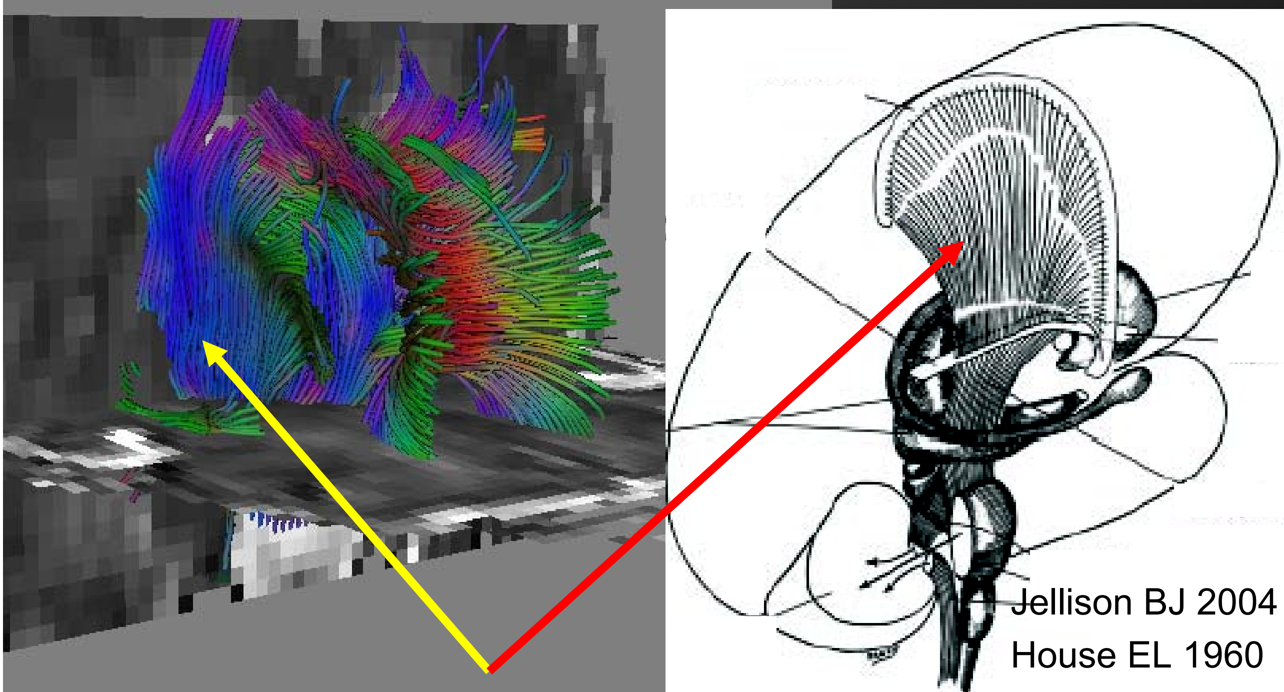
Adult vs. Newborn

Acquisition Difference with Adults:

- Fibers are less myelinated →less anisotropy → lower signal intensity
- Motion artifacts can play a larger role (scan within 4 minutes full-term newborns)
- The size of the pre-term (and neonatal) brain is smaller than of an adult. Voxel contains more structures than in an adult.
- The signal strength decreases if the voxelsize decreases.

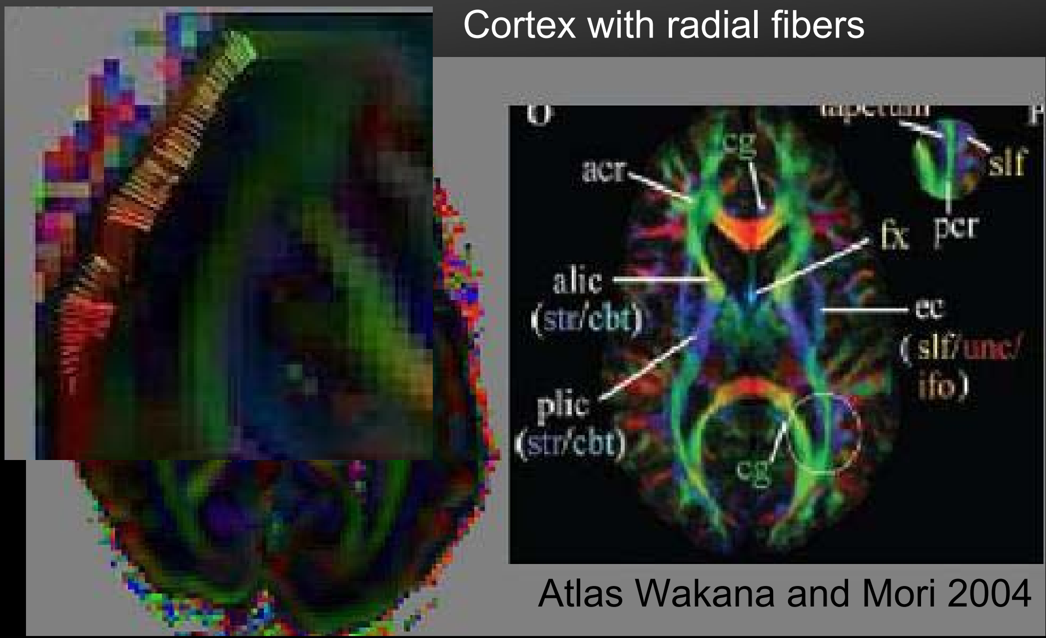
Visualization DTI: fiber tracking

Full term newborn at day 6



Example:
Adult vs.Premature Newborn

Cortex with radial fibers

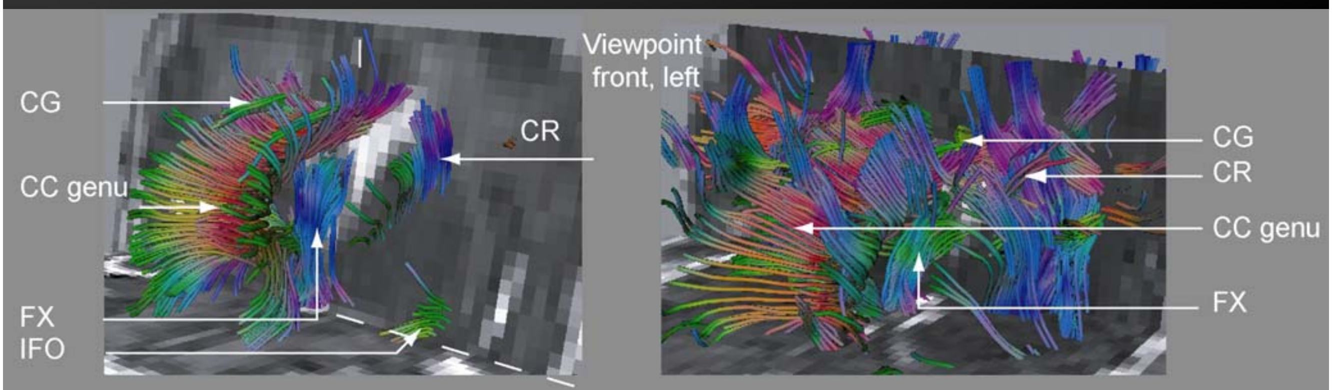


Atlas Wakana and Mori 2004

Premature Neonate (26 weeks)

Results:
normal newborns (follow ups)

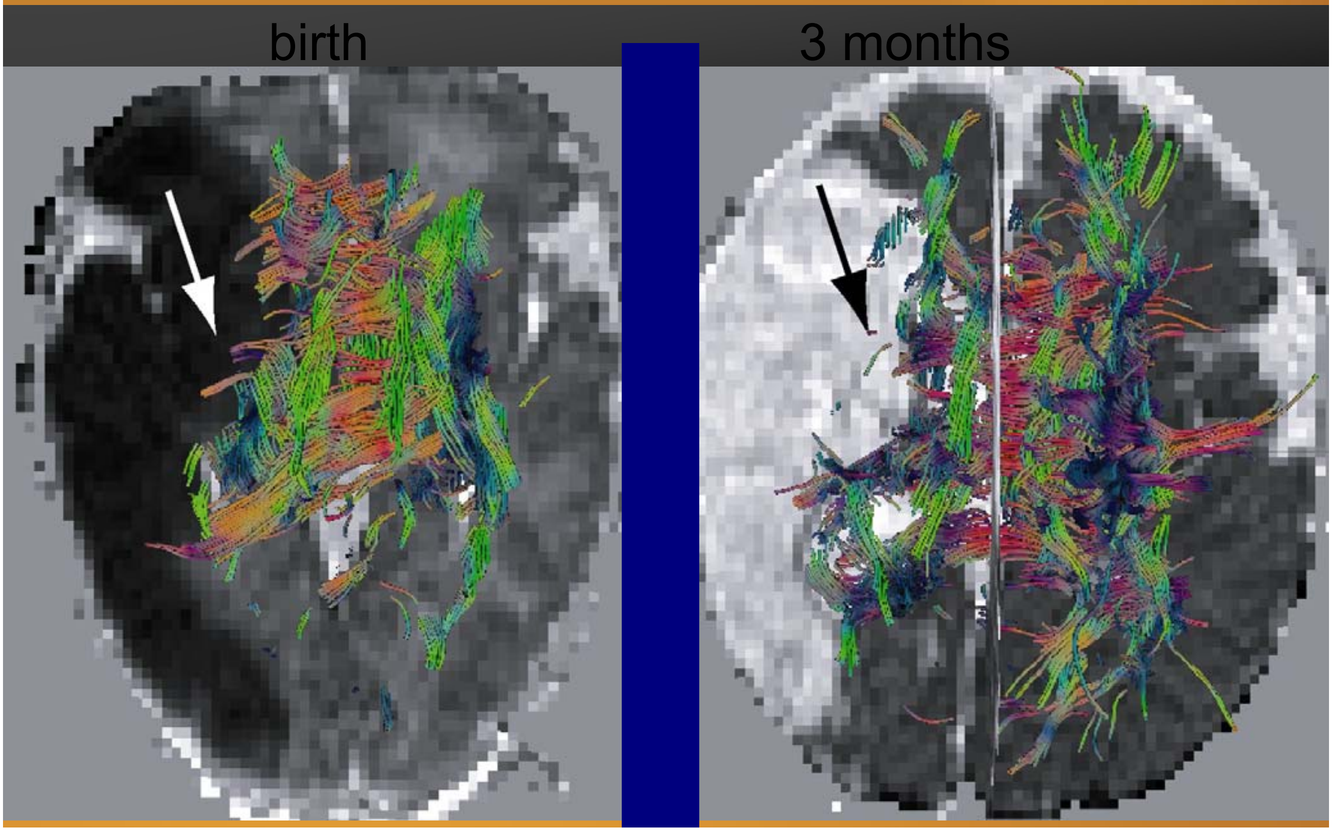
birth 3 months



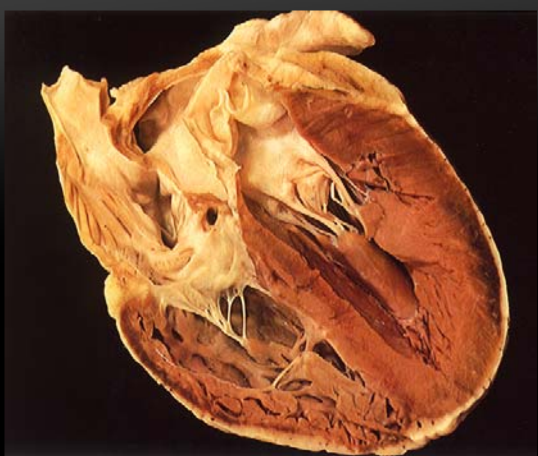
Which structures are developing and how?

Quantification?

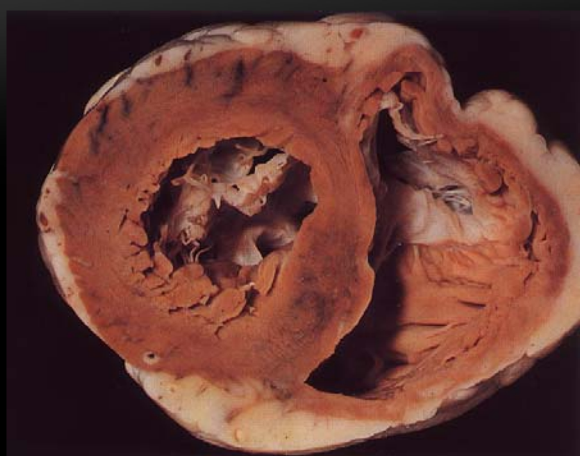
Results: newborns with pathology



Heart DTI visualization



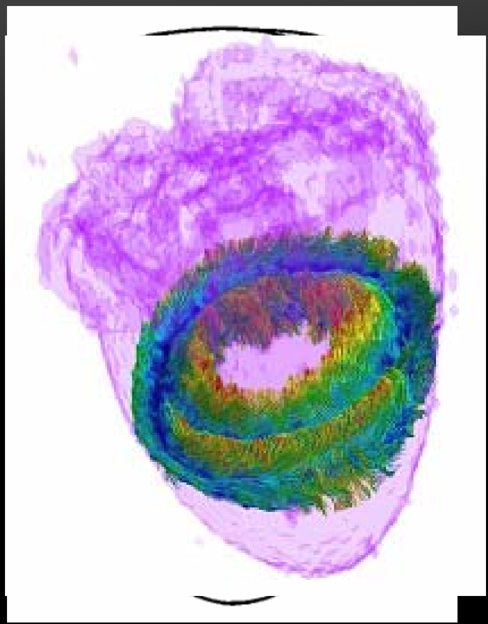
Sagittal section through the heart



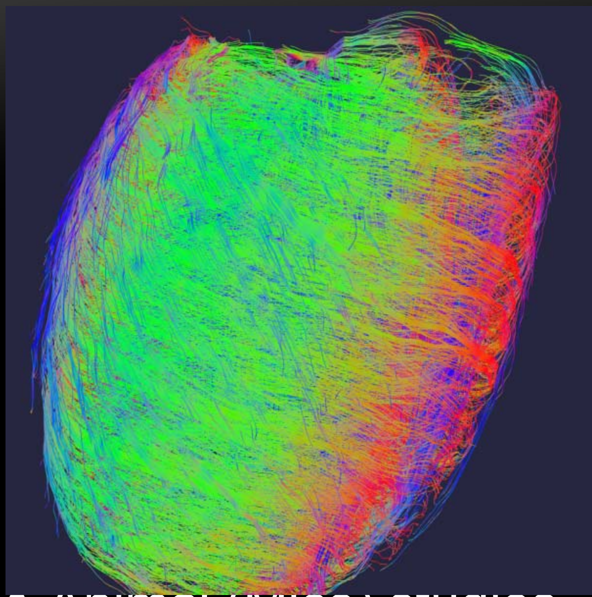
Short-axis section through the heart

[Anderson, 1980]

Heart



Model of Left Ventricle, depicting helix angle [Bovendeerd, 1992]

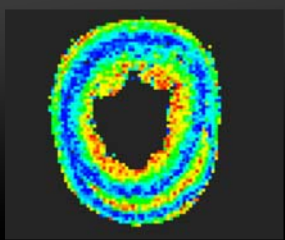


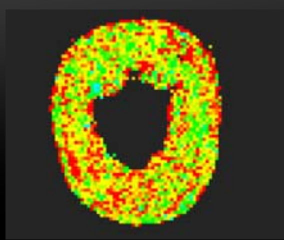
• Animal (Mice) studies

Visualization of the heart

Hue color mapping

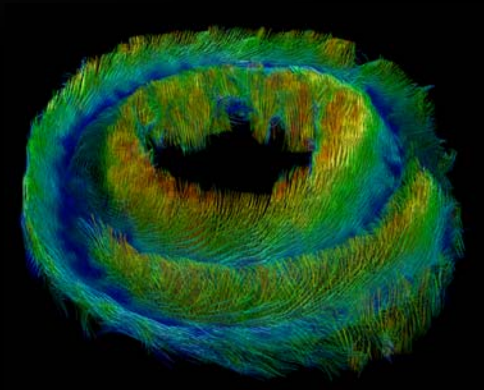
Helix Angle

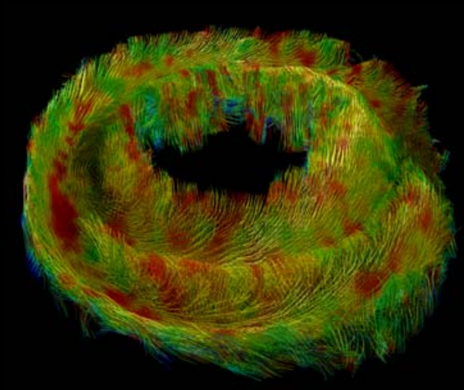




Hue color mapping

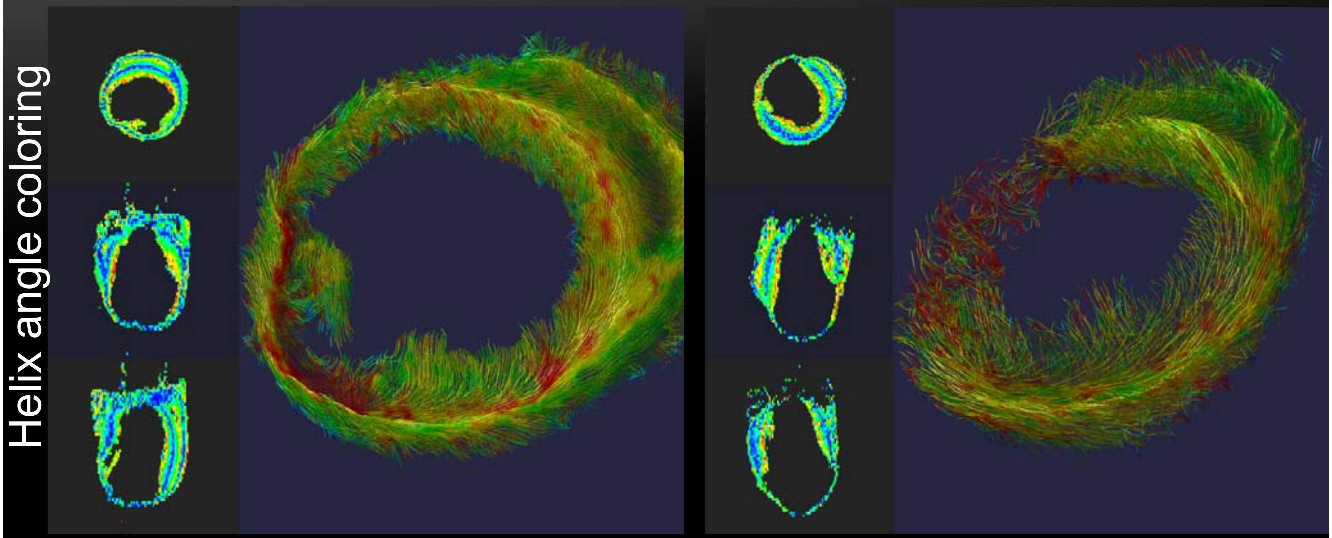
Fractional Anisotropy





Illuminated lines + Shadows

Fibers in a slice of ischemic mouse hearts



7 days
after infarct

28 days
after infarct

Ischemic hearts

In ischemic areas:

- Heart-wall becomes thinner
- FA becomes higher (this was unexpected)
- More random fiber orientations

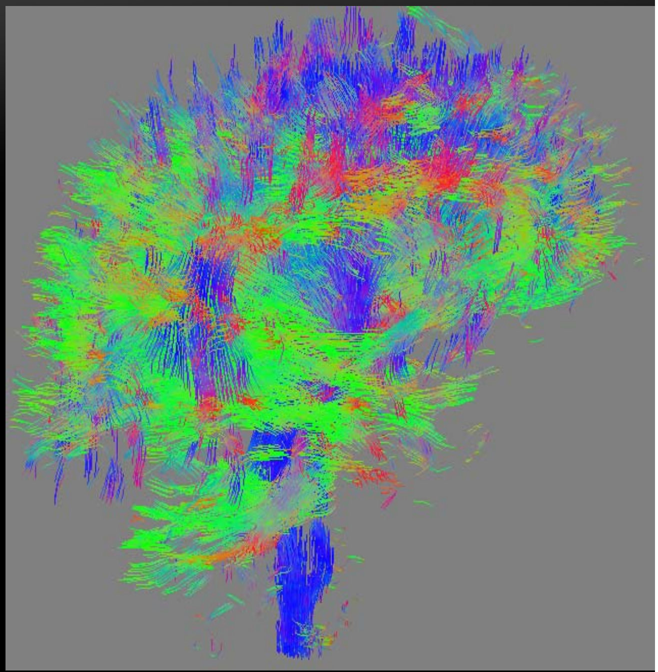
Conclusion: High FA and random fiber orientation probably caused by collagen fibers

Cluttering

Seed point definition
- Region of interest
  - Biased
  - Not reproducible
  - Miss information
- Whole volume
  - Cluttering

Individual “fibers” are of no interest

Bundles structures are of interest



Fiber Bundle

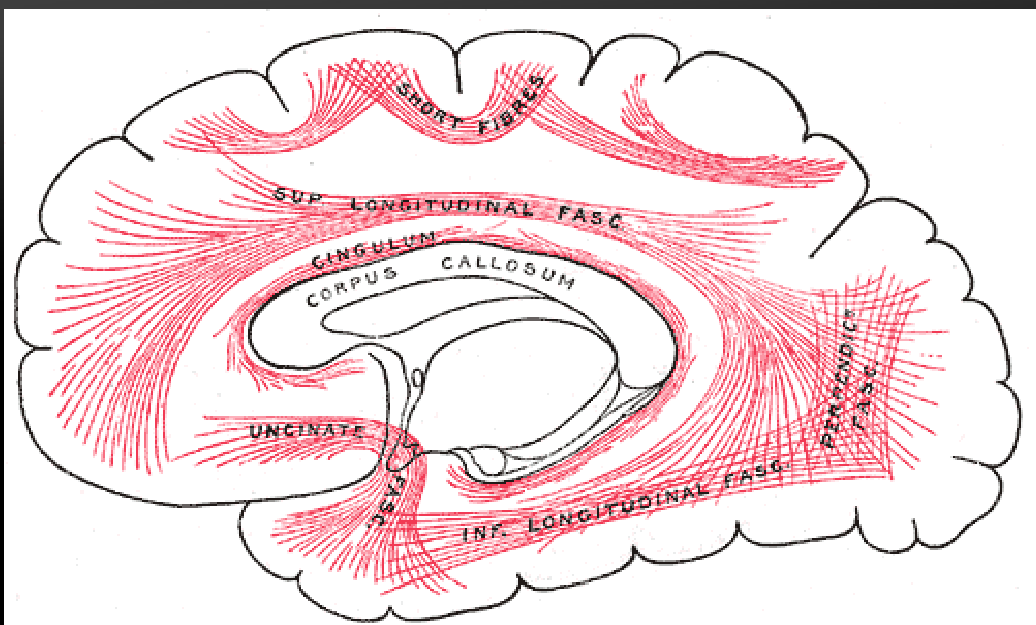


Image from Brun et al. 2003

Fiber Clustering

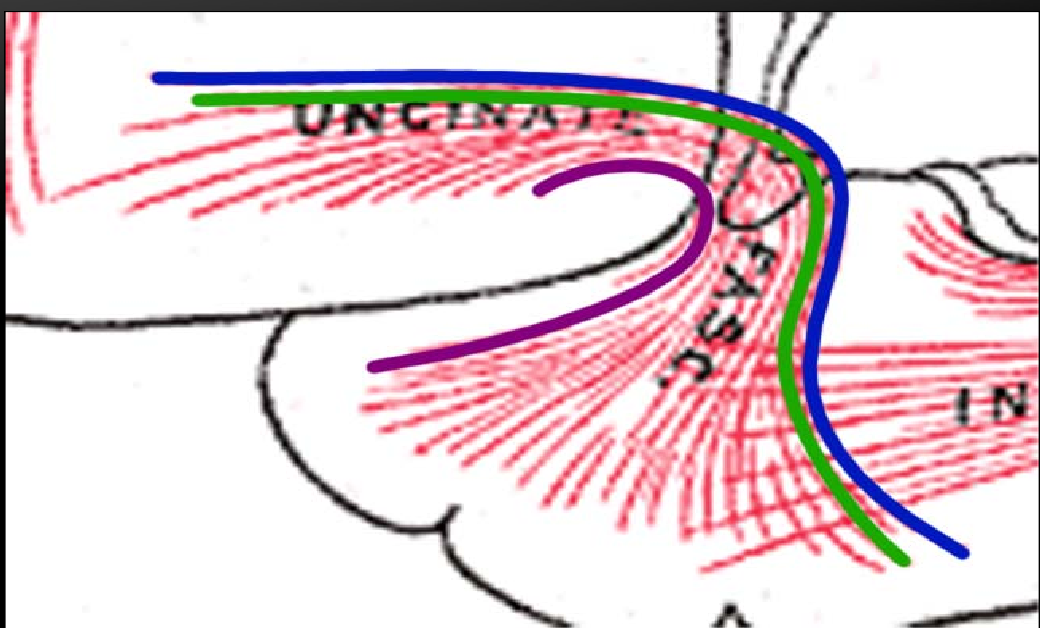
Group fibers together that are ***similar***

Form fiber bundles that are meaningful

Two problems:

- How to measure similarity between fibers?
- How to define the groups of fibers?

Fiber Bundle Properties

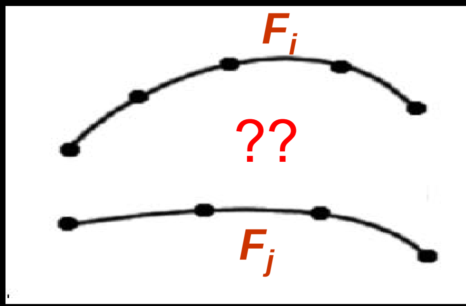


A lot of possible combinations

Ding et al. 01, Shimony et al. 02, Zhang et al. 02, Brun et al. 03, Brun et al. 04, Corouge et al. 04, etc.

There are a lot of similarity measures :

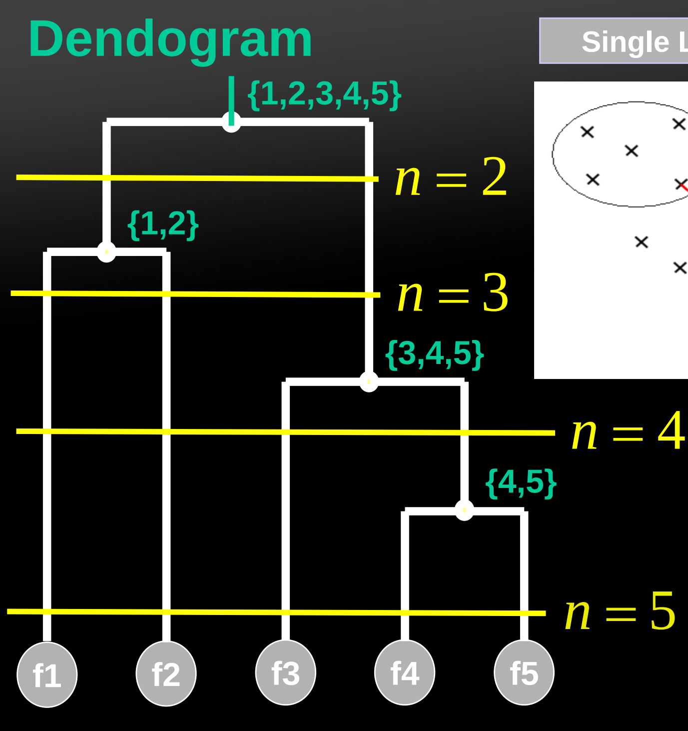
- Mean of closest points distance (Corouge et al. 04)
- Closest point distance (Corouge et al. 04)
- Hausdorff distance (Corouge et al. 04)
- End points distance (Brun et al. 03)
- ...



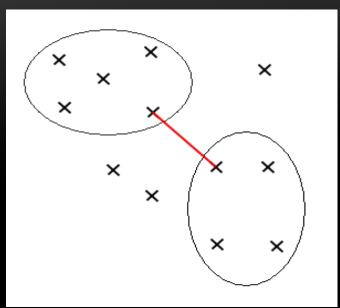
There are a lot of clustering algorithms:

- Hierarchical (Zhang et al. 02)
- Fuzzy c-means (Shimony et al. 02)
- Spectral clustering (O'Donnell and Westin 05)
- Shared nearest neighbor (Moberts et al. 05)
- ...

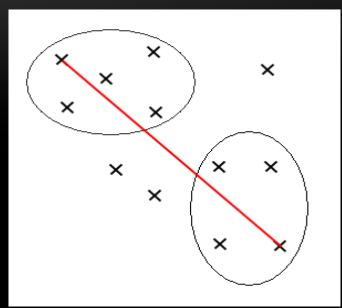
Example: Hierarchical Clustering



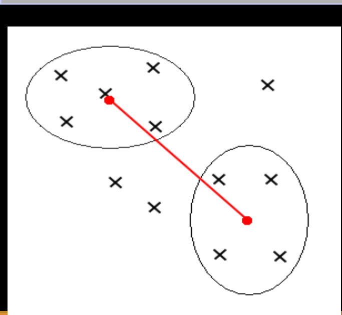
Single Link (HSL)



Complete Link (HCL)



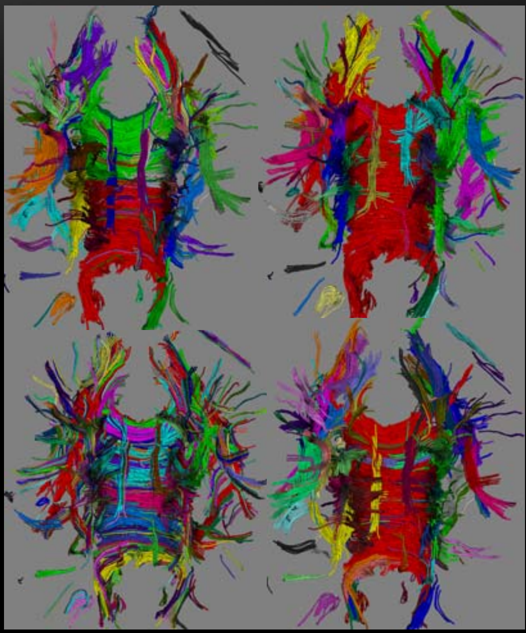
Weighted Average(HWA)



Validation

How do we know that ...

- ... a method is better than the other?
- ... a similarity measure is better than another?
- ... there is not a parameter setting giving better results?



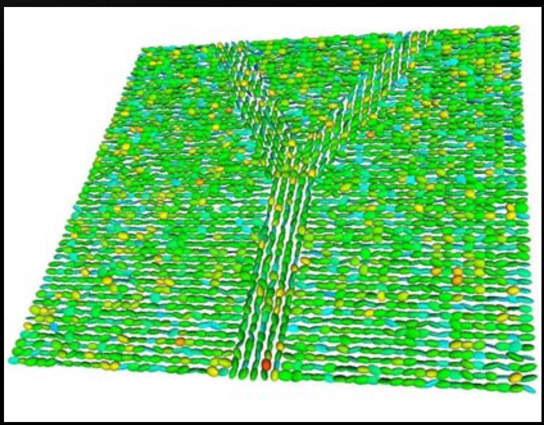
Validation [Moberts et al. 05]

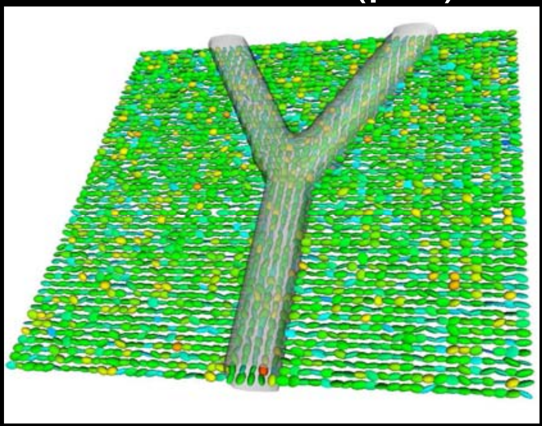
- Ground truth
- Comparison framework

Diffusion Tensor Imaging Segmentation

Fiber clustering depends on the fiber tracking algorithm and its parameter settings.

Can we directly segment the tensor fields (pdf)?



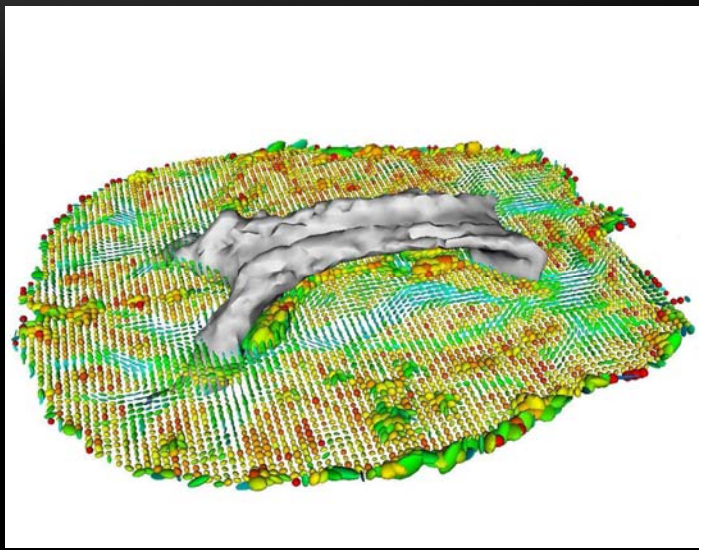


Images from [Lenglet et al. 04]

Diffusion Tensor Imaging Segmentation

There exist several segmentation techniques for scalars:

- Thresholding: ordering of the tensors
- Region based: definition of homogeniety (e.g. Ziyan et al 06, Bartesaghi and Nadar 06)
- Edge based: definition of gradient in the tensor field
- Defomable Models: definition of forces and energies based on the tensor field (e.g., Lenglet et al 06, Wang et al. 05, Schultz et al. 06)
- ...



Corpus callosum segmentation using level sets technic
Images from [Lenglet et al. 04]

Tensor similarity or distance

You want to group diffusion tensors that are similar.

Given tensor A and B, How similar (different) are they?

- Linear Algebra- tensor is a 6D vector . Example:

$$d_{L2}(\mathbf{A},\mathbf{B}) = \sqrt{\sum_{i=1}^{3}\sum_{j=1}^{3}(\mathbf{A}_{ij}-\mathbf{B}_{ij})^2}$$

- Riemannian geometry- geodesic distance in the space of positive definite matrices.

$$d_g(\mathbf{A},\mathbf{B}) = N(\mathbf{A}^{-\frac{1}{2}}\mathbf{B}\mathbf{A}^{-\frac{1}{2}})$$

$$N(\mathbf{D}) = \sqrt{\sum_{i=1}^{3}(\log(\lambda_i^{\mathbf{D}}))^2}$$

Approximation Log-Euclidean distance

$$d_{LE}(\mathbf{A},\mathbf{B}) = \sqrt{\mathrm{tr}((\log(\mathbf{A})-\log(\mathbf{B}))^2)}$$

Tensor similarity or distance

- Probability density functions (pdf)– overalap of the pdf using A and B as covariant matrices of Gaussians
  - Kullback-Leibler (KL) distance

$$d_{KL}(\mathbf{A},\mathbf{B}) = \frac{1}{2}\sqrt{\mathrm{tr}(\mathbf{A}^{-1}\mathbf{B}+\mathbf{B}^{-1}\mathbf{A})-2n}$$

n is 3

  - Class separability Bhattacharyya bound

$$S_{Bhat}(\mathbf{A},\mathbf{B}) = e^{-\frac{1}{2}ln\left(\frac{\det(\mathbf{AB})/2}{\sqrt{\det(\mathbf{A})\det(\mathbf{B})}}\right)}$$

- Anisotropy Indices – use anisotropy indices FA, CI or any combination of those
- Angular differences – Use the angular difference between the main eigenvectors (dot product)

DTI Segmentation

- What measure or method to use depends on the problem (e.g.,bundle)
- Segmentation is an active field of research for scalar fields. Extention to tensor fields is a challenge
- These methods use the full information of the tensor and can be more robust and reproducible than fiber clustering techniques
- No much has been done in this field yet

Overview

- DiffusionTensor Imaging data
- DTI Visualization techniques
- Applications: newborn and ischemic heart
- Fiber clustering
- Diffusion tensor field segmentation

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