Scientific Visualization
and Computer Graphics
University of Groningen

Information Visualization in Neuroscience

Jos Roerdink

Johann Bernoulli Institute for Mathematics and Computer Science, University of Groningen &
BCN Neuroimaging Center, University Medical Center Groningen

university of groningen

http://www.cs.rug.nl/svcg/

Visualization

university of groningen

Dictionary definitions:

visualize: to form a mental image or vision of …
visualize: to imagine or remember as if actually seeing

Structuring and expressing data in a visual way to obtain useful information

Brain Connectivity

Special issue on

Functional Connectivity

E. Bullmore,L. Harrison,

L. Lee, A. Mechelli, K. Friston

(eds.)

Vol. 2, No. 2, 2004

Connectivity Types

university of groningen

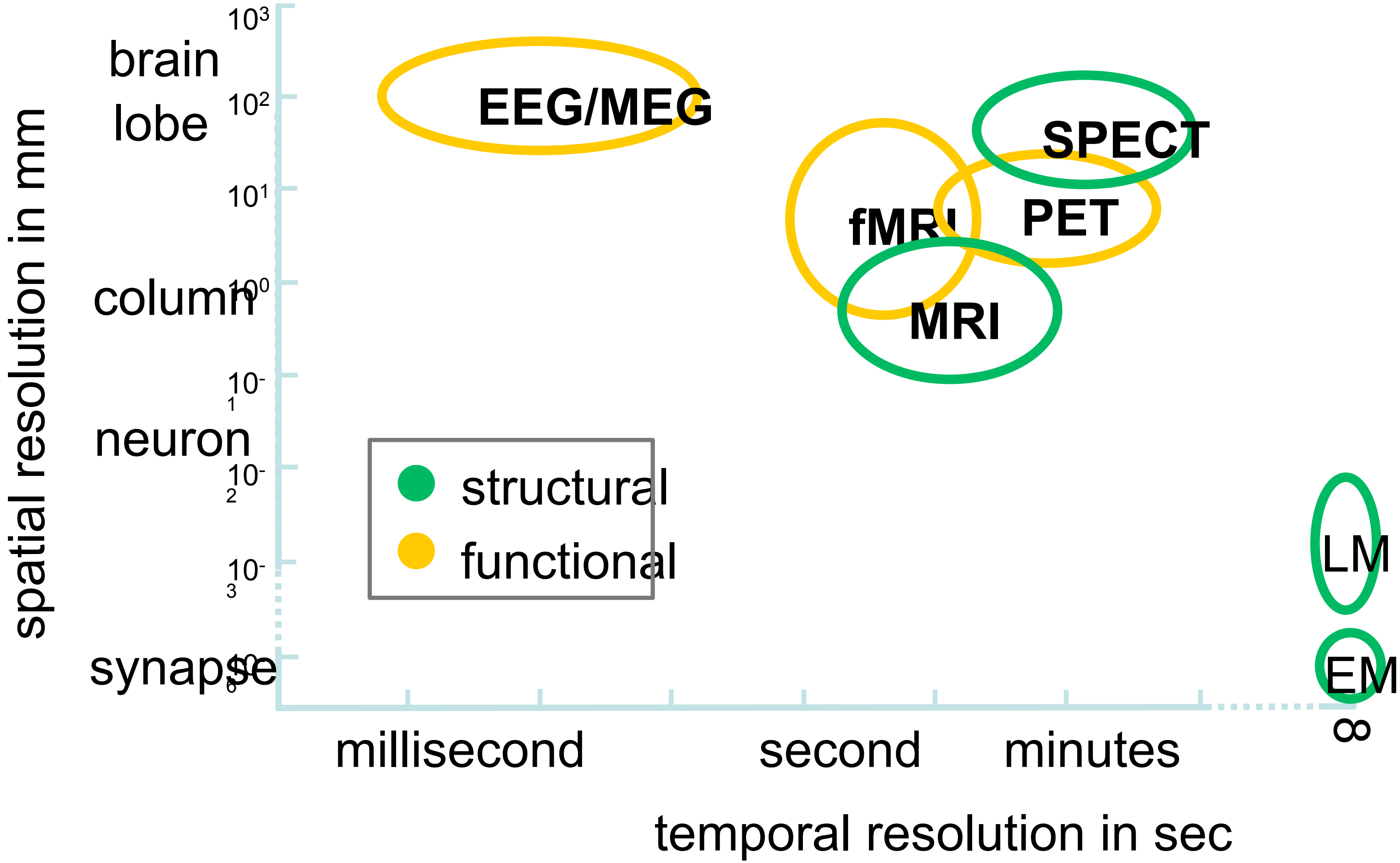
- Anatomical Connectivity
- Functional Connectivity (statistical dependencies)
- Effective Connectivity (causal interactions)

Connectomics

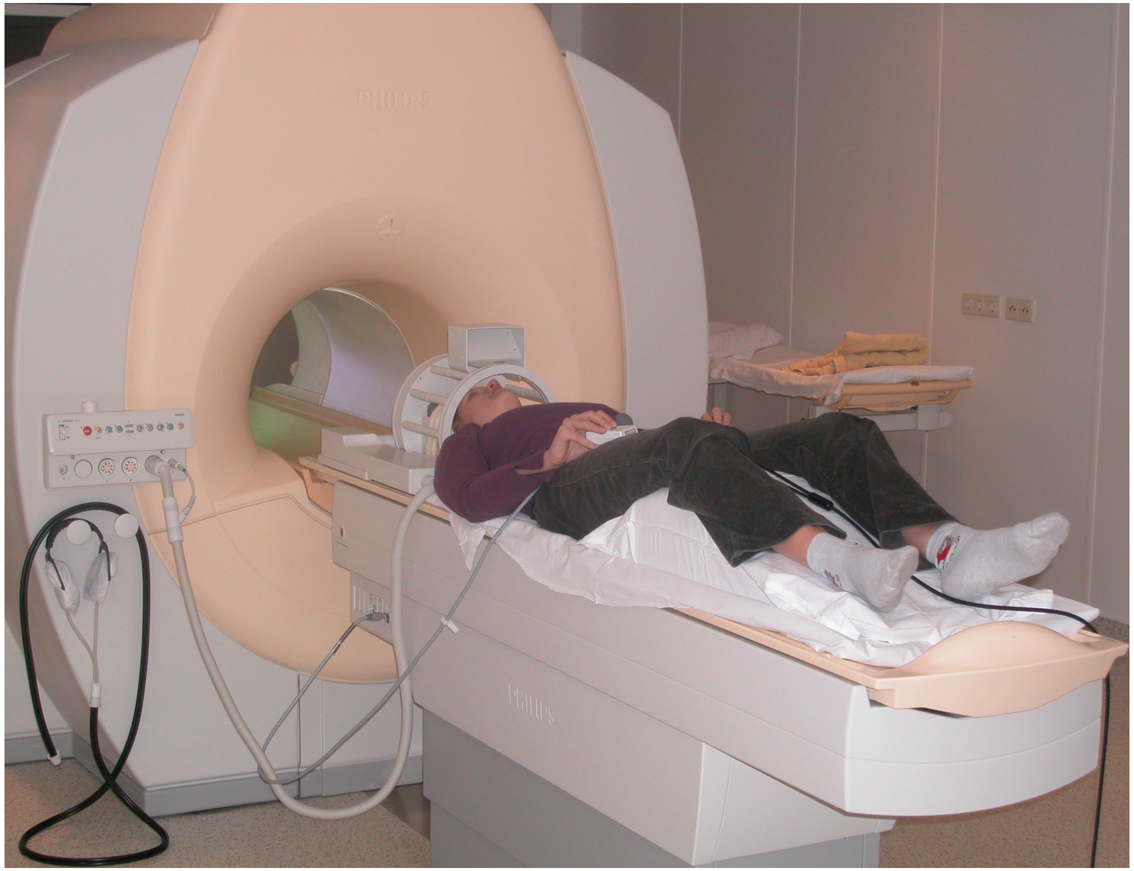
- **Macroscale**: anatomically distinct brain areas with specific patterns of interconnectivity (millimeter scale)
- **Mesoscale**: local neuronal circuits, cortical columns (micrometer scale)
- **Microscale**: single neurons and their connectivity patterns

Sporns, O., Tononi, G., Kötter, R.: The Human Connectome: A Structural Description of the Human Brain. PLoS Computational Biology 1(4), e42 (2005)

Imaging Modalities

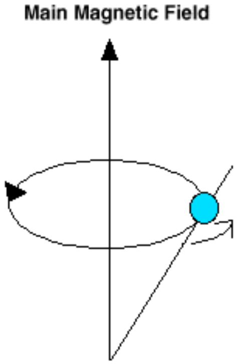


Functional MRI

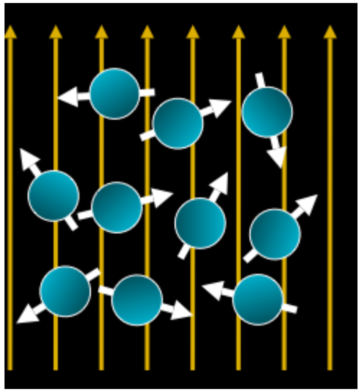


3 Tesla MRI scanner

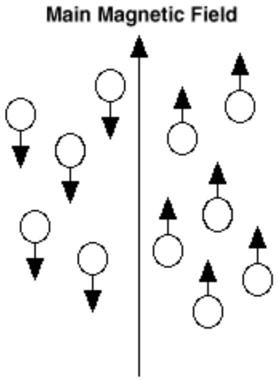
How MRI works



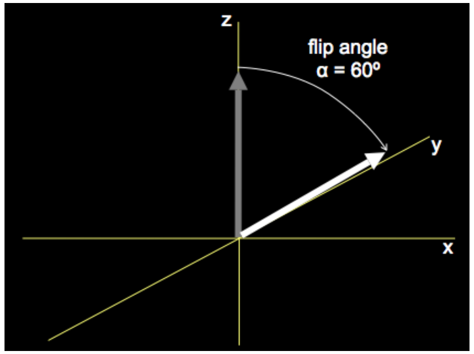
Atom precession



Without external field

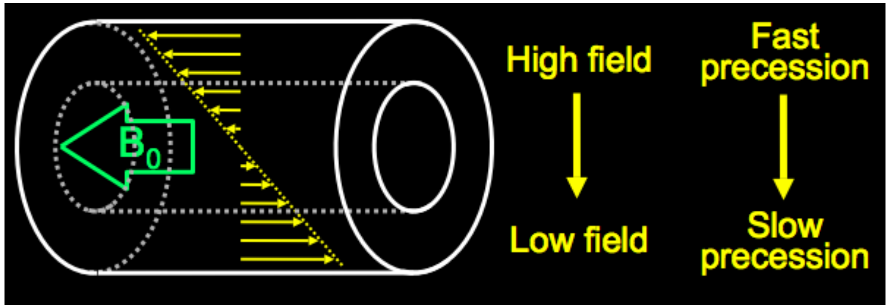


With external field

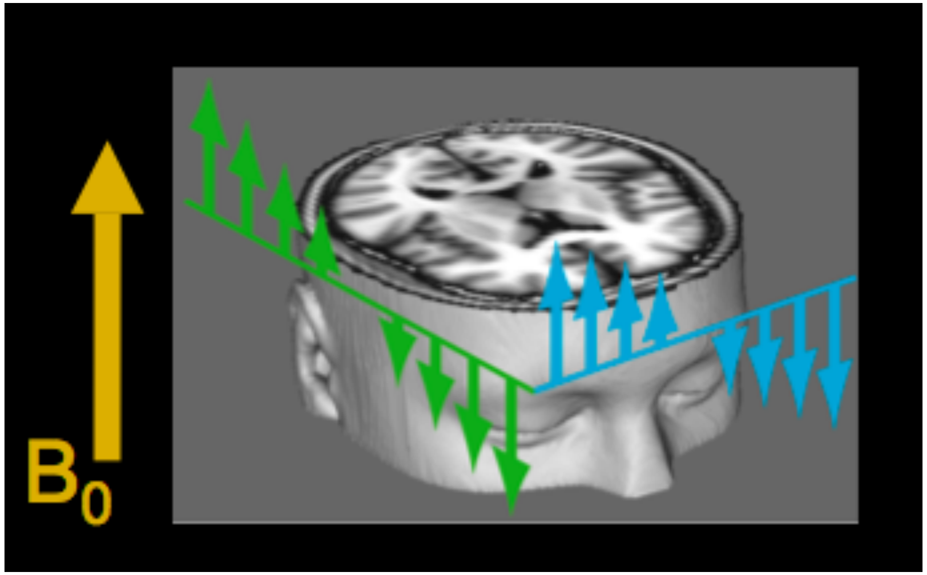


Out of equilibrium after RF pulse

How MRI works

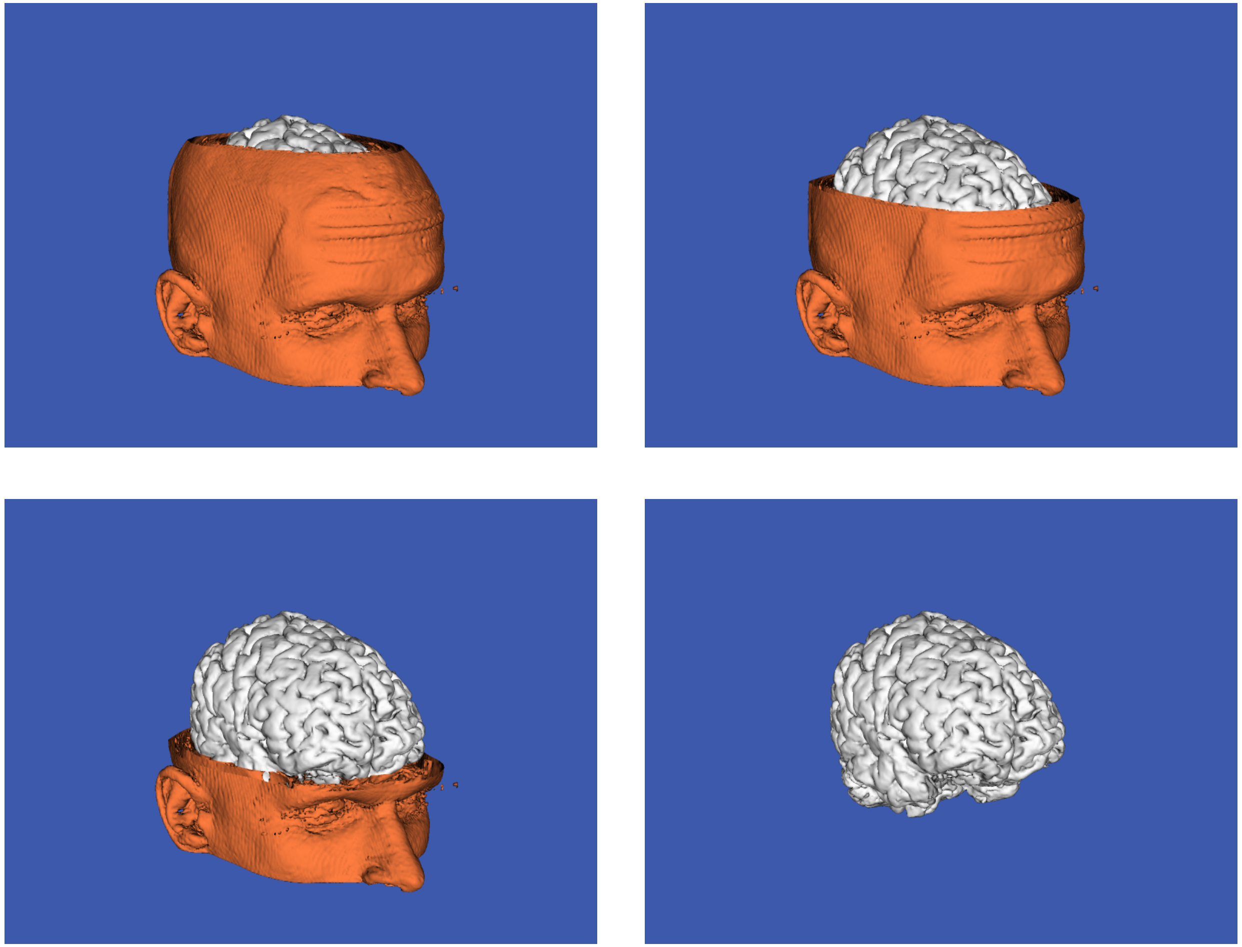


Spins at different frequency



Making an image with varying gradient fields

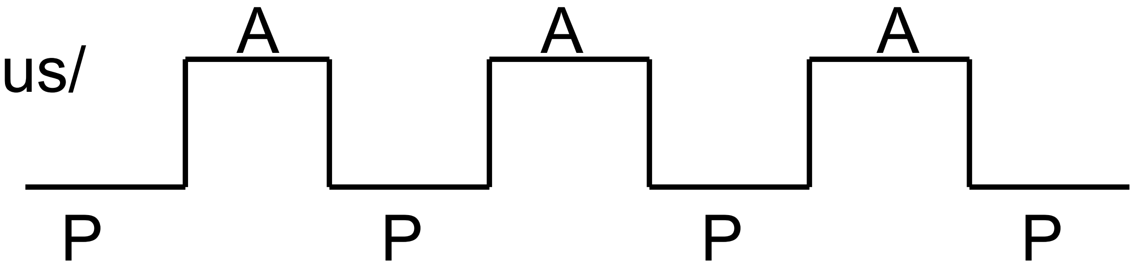
Cortex extraction



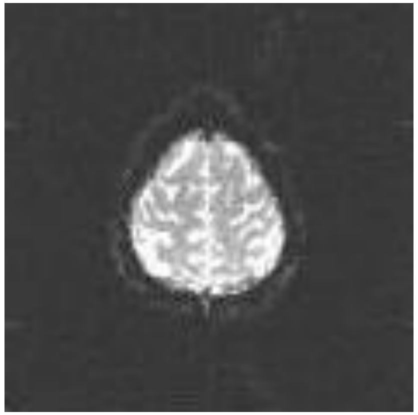
Cortex extraction by morphological filtering

Functional brain mapping

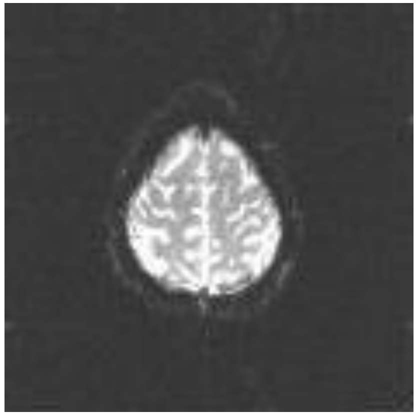
Stimulus/ task



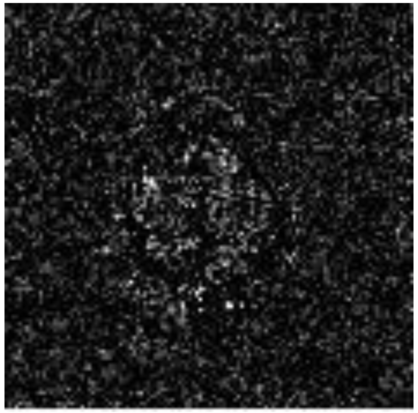
A=Active
P=Passive



Active

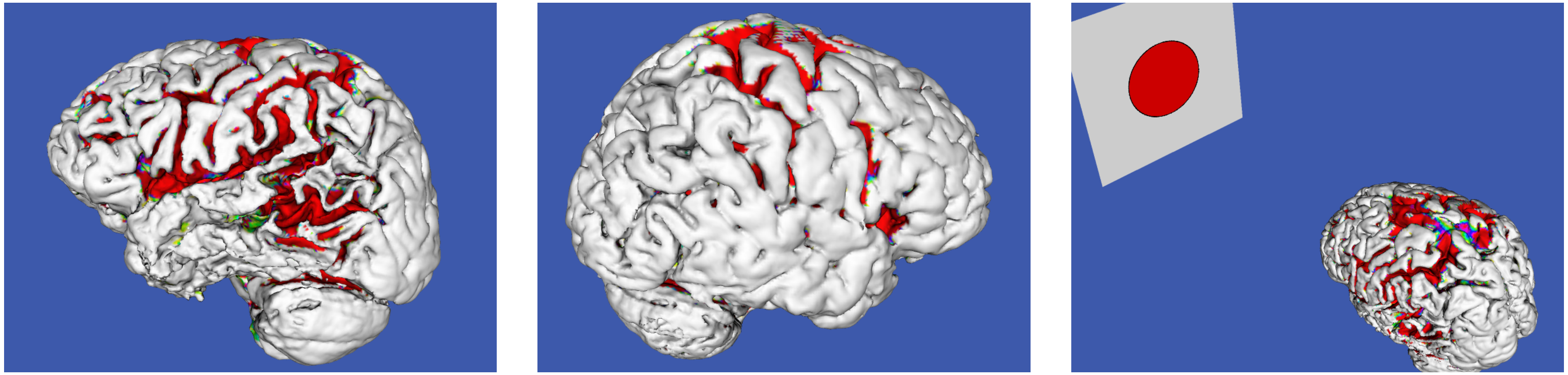


Passive



Difference

Functional MRI visualization



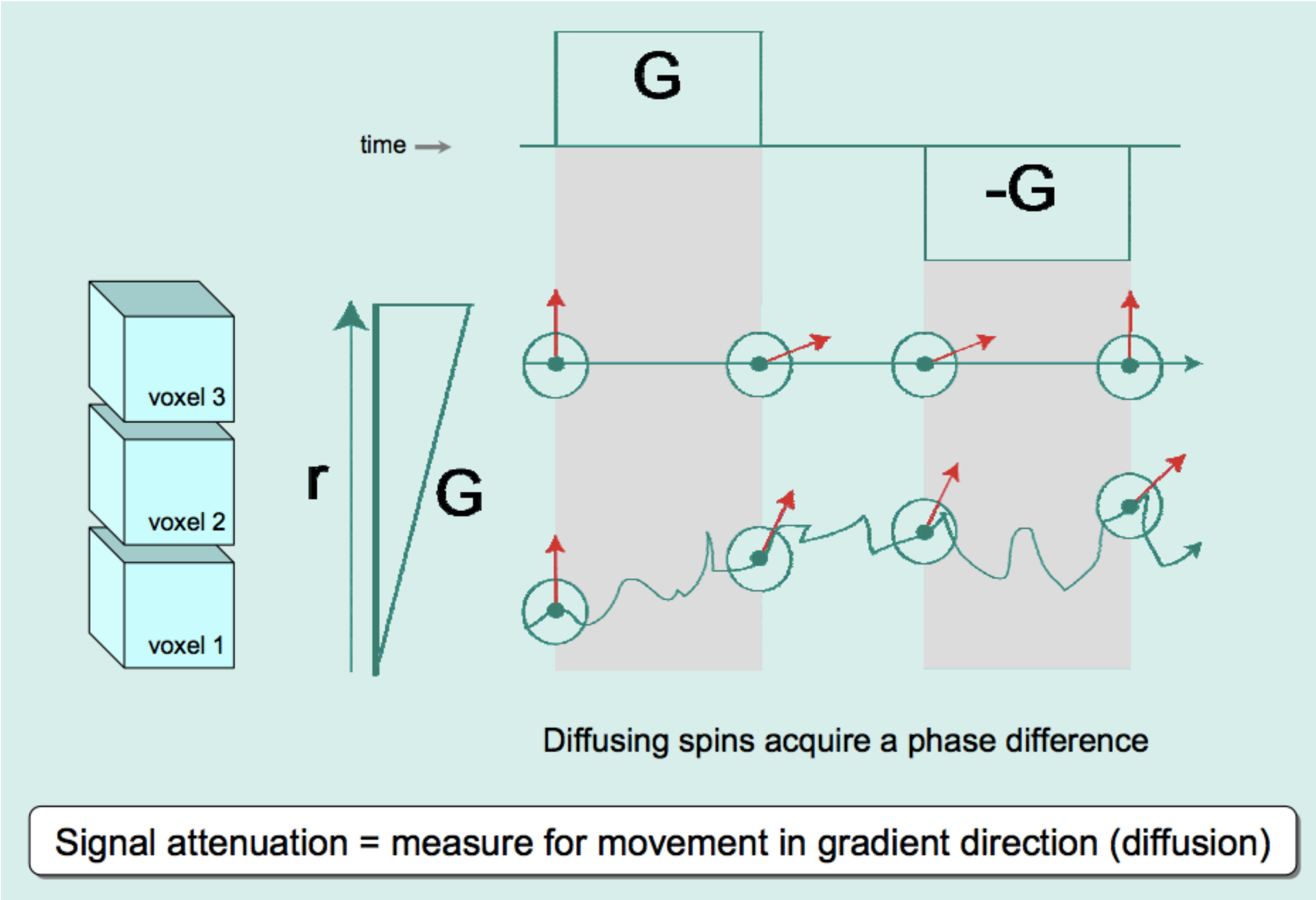
Visualization of brain activation during finger tapping elicited by a visual stimulus. Main activation occurs in motor cortex and visual cortex.

Based on normal fusion (Stokking et al., J. Nuclear Medicine 38, 624-629, 1997)

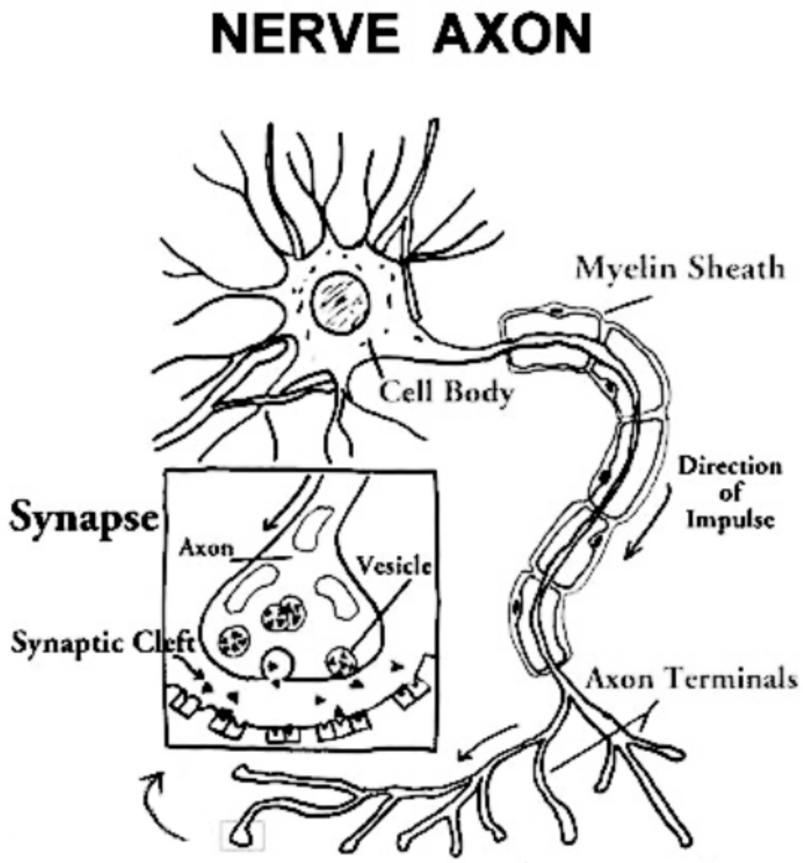
Diffusion-Weighted MRI (DW-MRI)

Diffusion Tensor Imaging (DTI)

Basis of DW-MRI

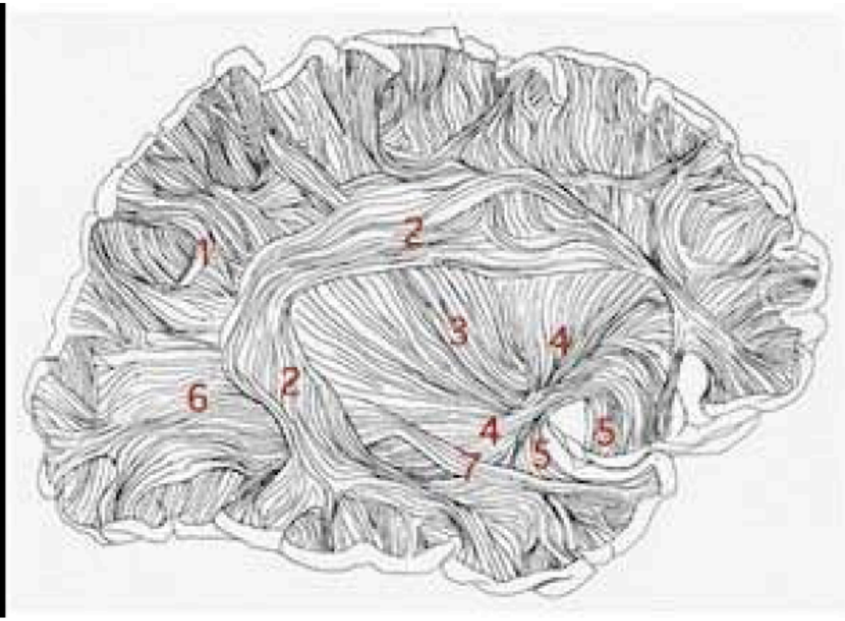


Brain white matter structure



Neuron with an axon surrounded by a myelin sheath.
Inset: details of a synapse in one of the axon terminals

Fiber Bundles in the Brain



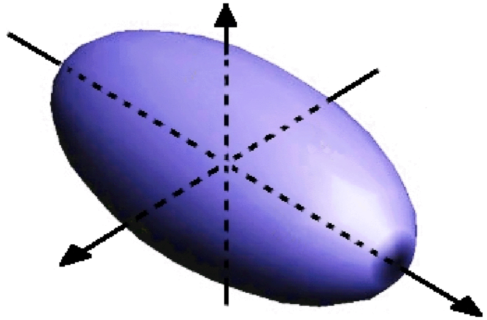
1. Short acruate bundles. 2. Superior longitudinal fasciculus. 3. External capsule. 4. Inferior occipitofrontal fasciculus. 5. Uncinate fasciculus. 6. Sagittal stratum. 7. Inferior longitudinal fasciculus.

(Poupun et al., MICCAI 1999)

Diffusion-tensor imaging

Directional diffusion of water can be described by a diffusion tensor, i.e., a symmetric 3×3 matrix:

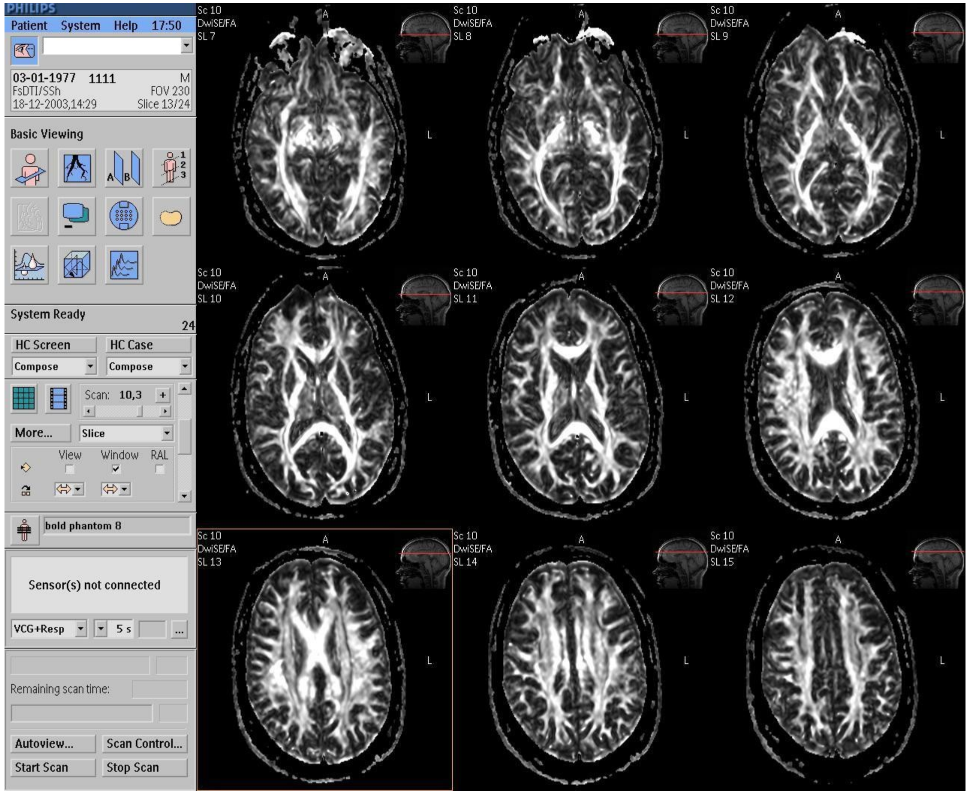
$$\mathbf{D} = \begin{pmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{pmatrix}$$



diffusion ellipsoid

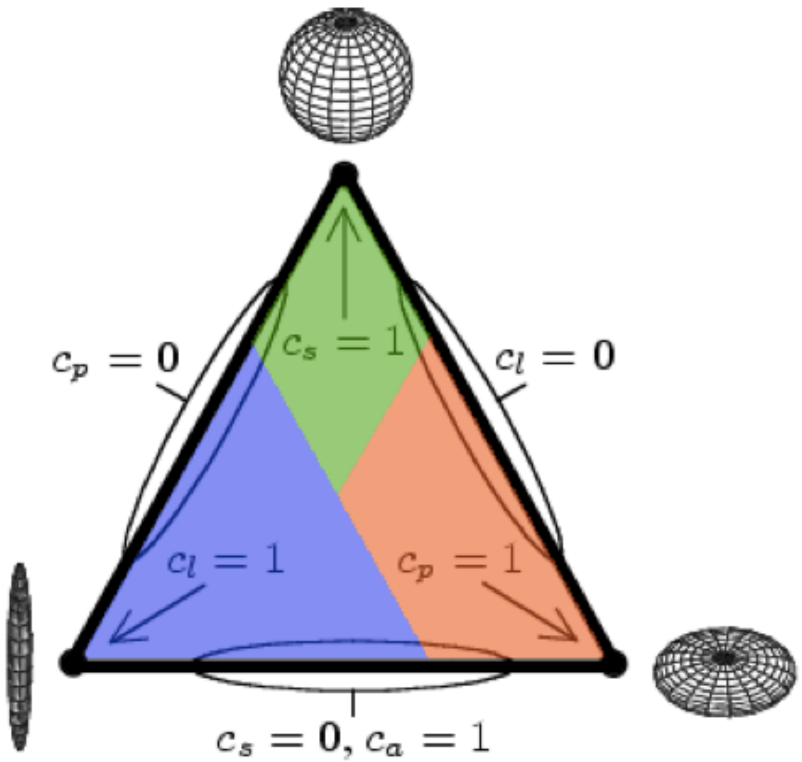
$$P(\mathbf{r},\tau) = \left(\det \mathbf{D}(4\pi\tau)^3\right)^{-\frac{1}{2}} \exp\left(-\frac{\mathbf{r}^T\mathbf{D}^{-1}\mathbf{r}}{4\tau}\right)$$

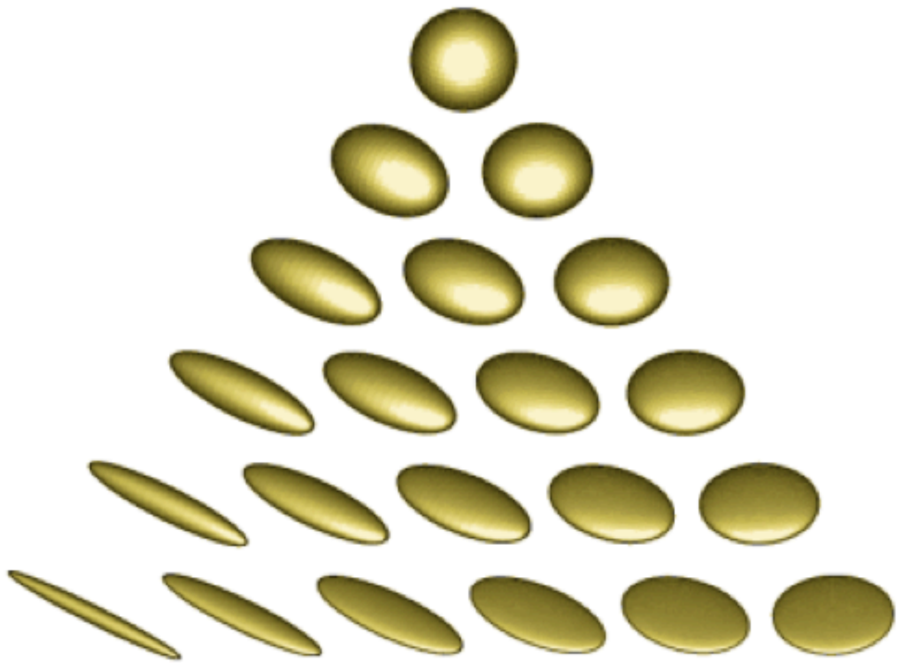
Diffusion-tensor imaging



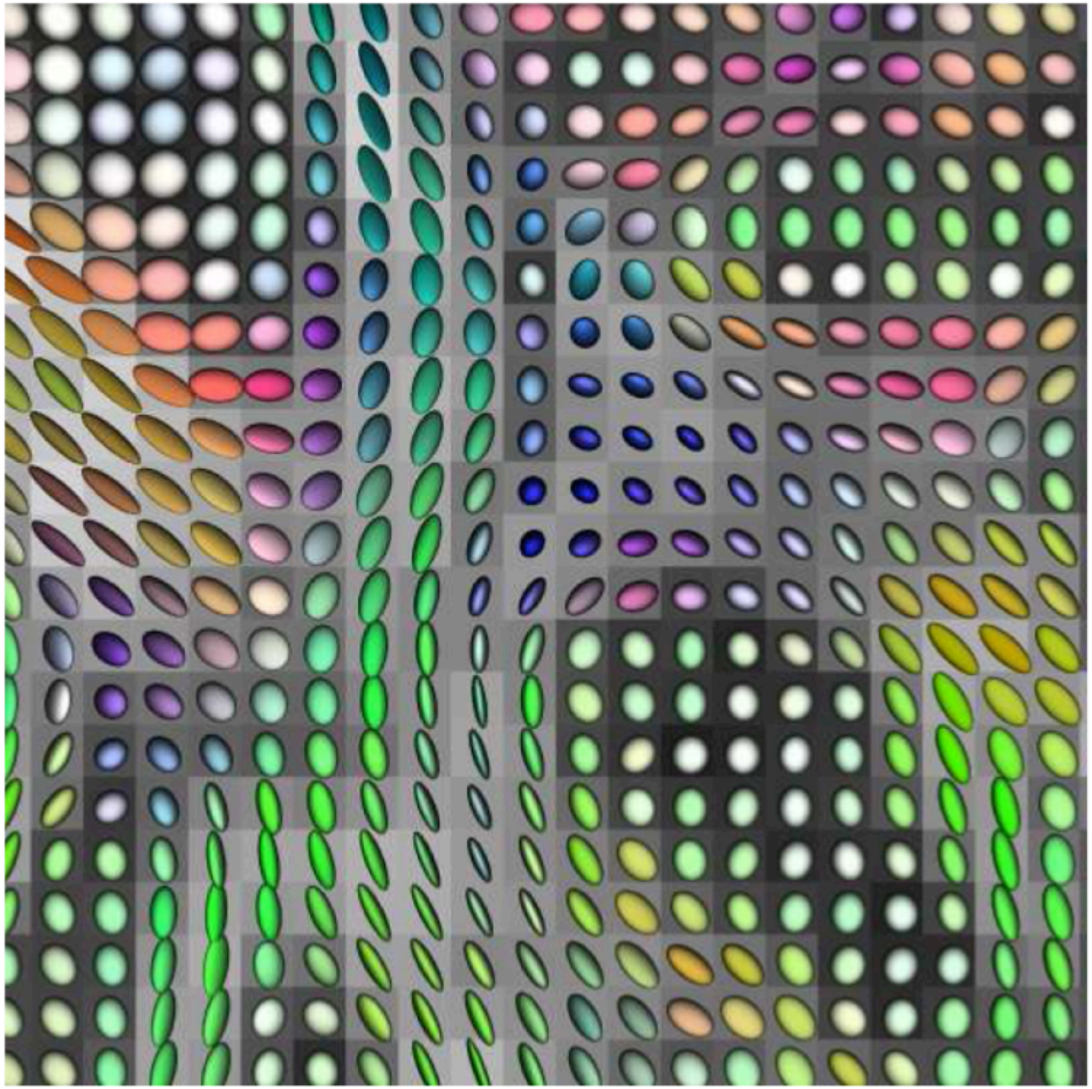
D can be solved by measuring at least 6 different diffusion weighted images + 1 unweighted image

Barycentric coordinate system

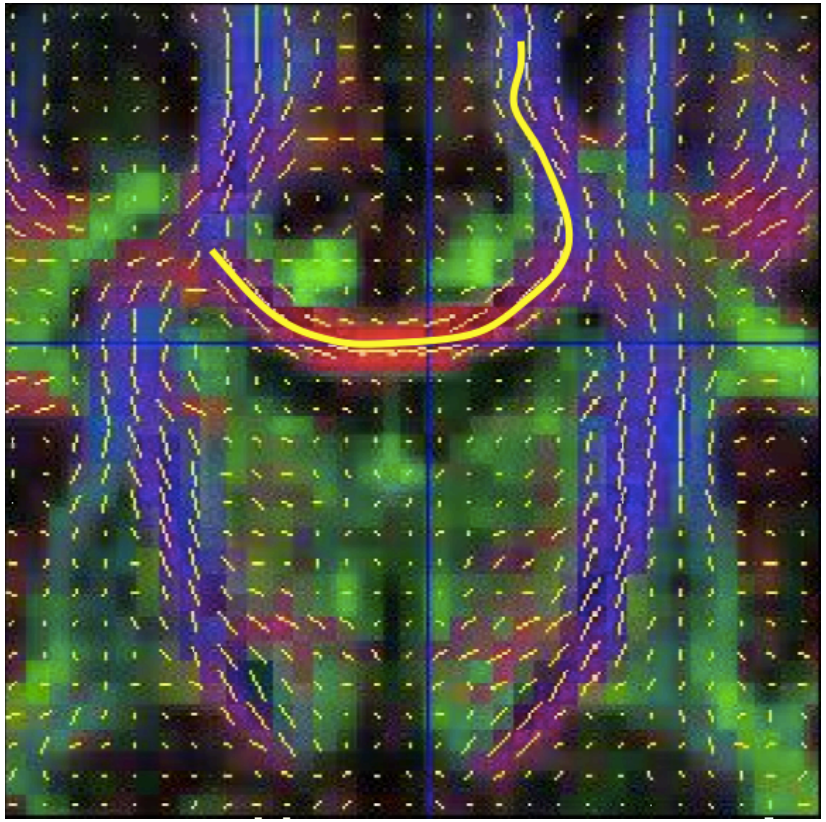




Ellipsoidal Glyph Representation



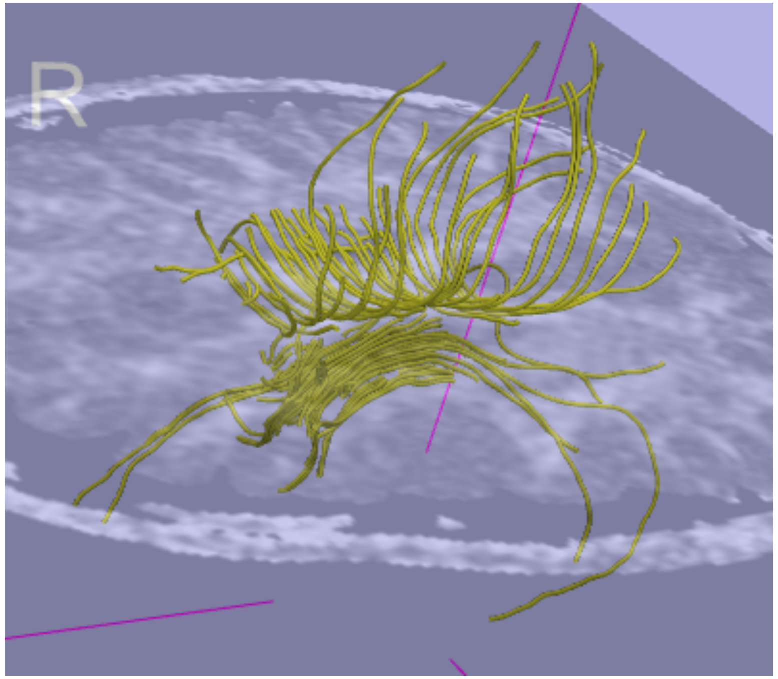
Fiber tracking (tractography)



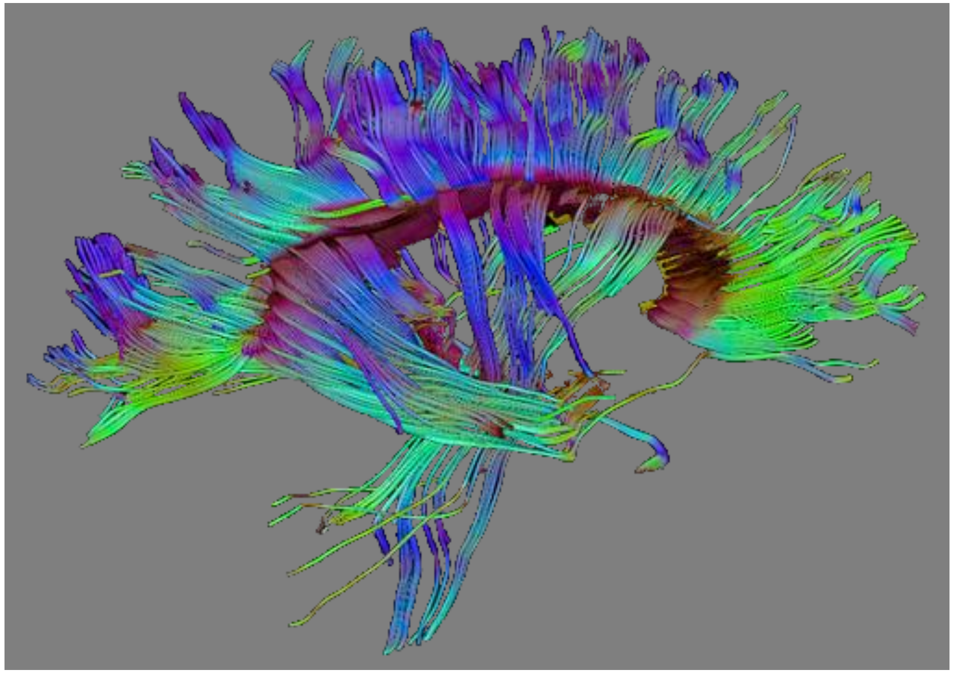
$$\frac{d\mathbf{r}(t)}{dt} = \mathbf{v}(t)$$

Line propagation methods are based on following a path according to some propagator, e.g., main eigen-direction

Tractography



Fiber tracts from the corpus callosum



Fiber tracts coloured by anisotropy direction

Follow the direction of the dominant eigenvector of **D** in each voxel.

Illustrative Rendering: Depth-Dependent Halos

Maarten Everts, Henk Bekker, Jos B.T.M. Roerdink, and Tobias Isenberg
IEEE Vis 2009
www.cs.rug.nl/~isenberg/VideosAndDemos/Everts2009DDH

Multichannel EEG coherence network visualization

Joint work with Department of Neurology (Natasha Maurits) & Department of Experimental and Work Psychology (Monicque Lorist)

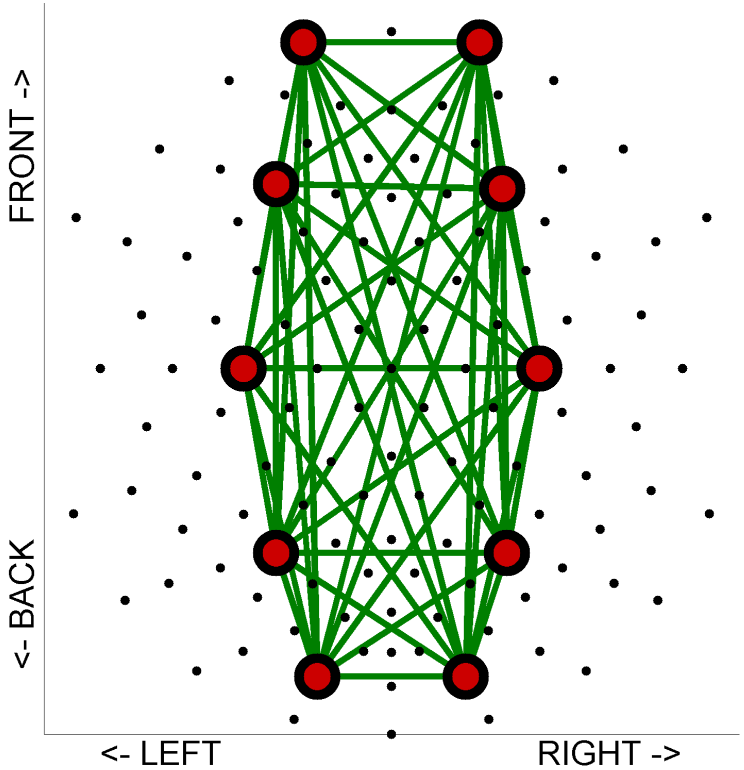
EEG coherence

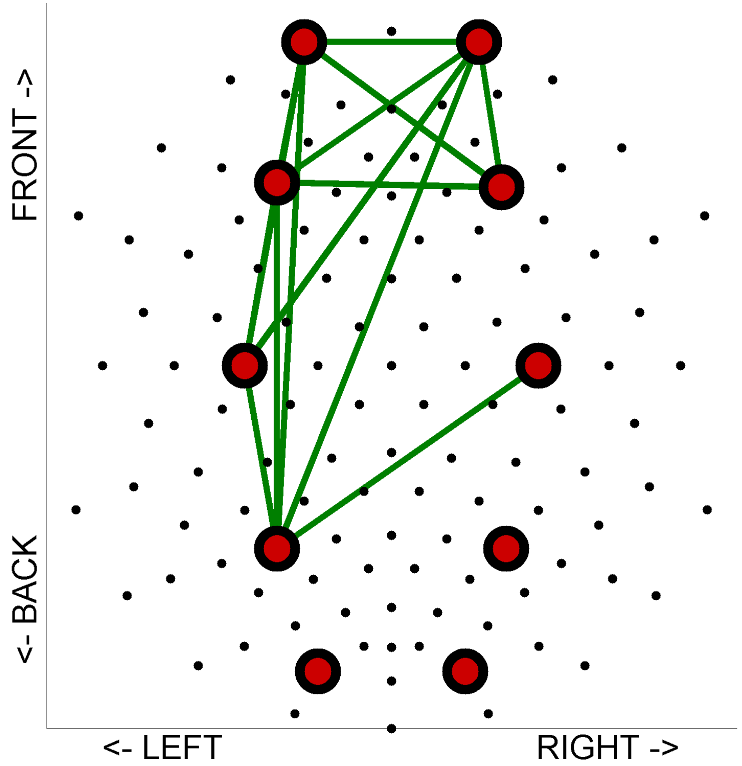
- Synchronous electrical activity between brain regions is assumed to imply functional relationships between these regions
- Measure for this synchrony: EEG coherence as a function of frequency
- Conventional visualization is hypothesis-driven
- New method: data-driven graph visualization method

M. Ten Caat, N. Maurits, J. Roerdink
IEEE TVCG 14 (4), 2008, pp. 756-771

Conventional hypothesis-driven visualization

Frequency: 1-3 Hz 13-20 Hz

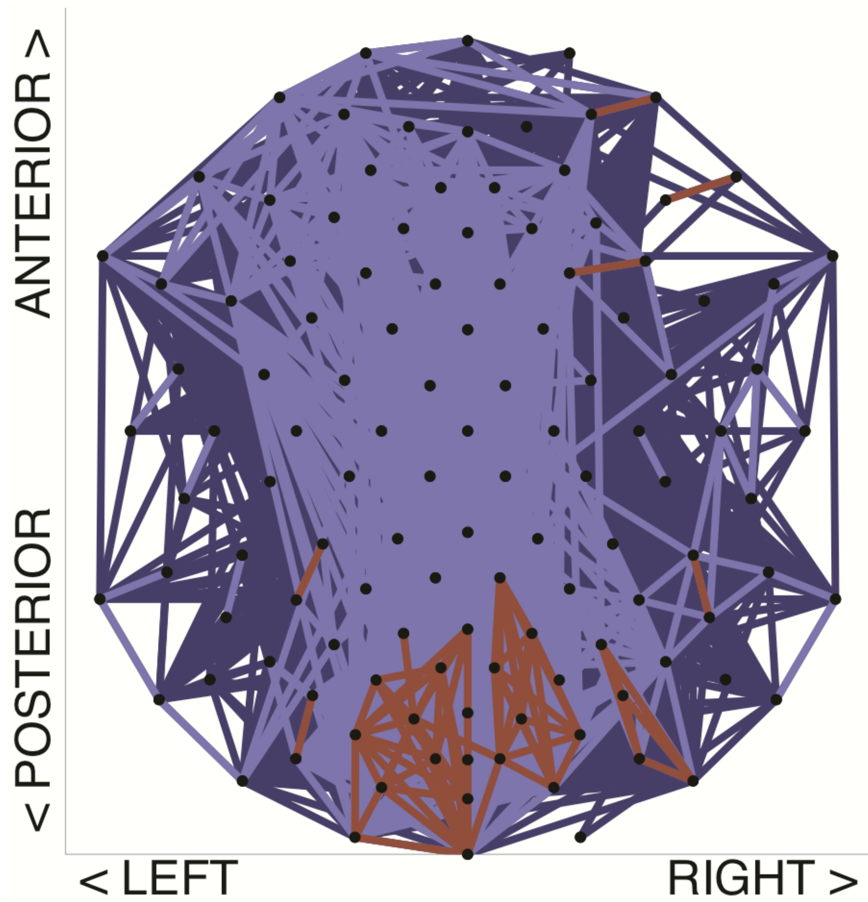




Graph: dots represent electrodes, lines significant coherences:

- 10 red electrodes selected out of 119 electrodes (8 %)
- 45 coherences studied out of 7021 coherences (0.6%)

Conventional data-driven visualization

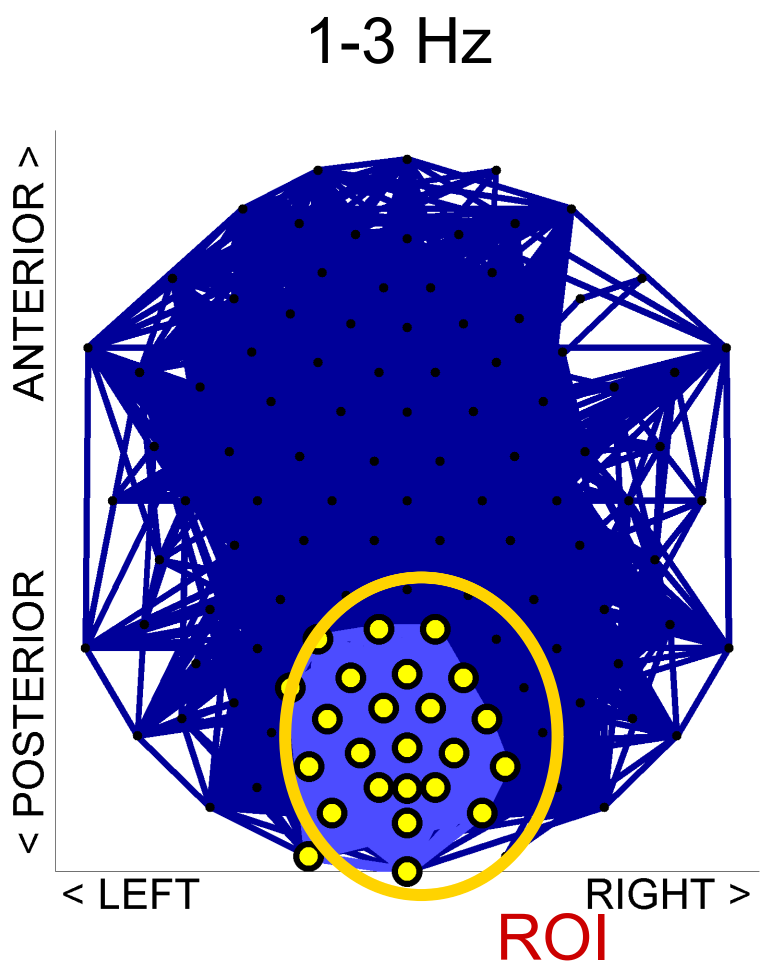


	significance threshold	coh > 0.15
	top 10%	coh > 0.37
	top 1%	coh > 0.91

All electrodes and all significant coherences

Result: visually cluttered edges

Data-driven ROI: Functional Unit (FU)



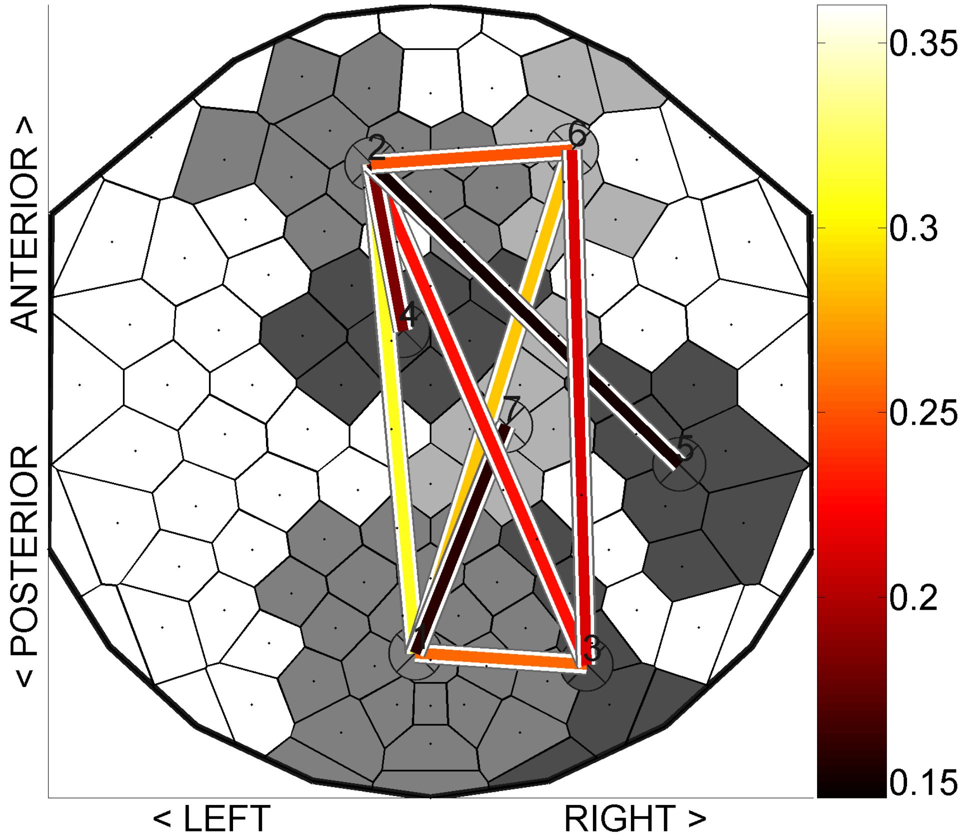
Functional Unit (FU):
spatially connected clique

(clique = maximally connected subgraph)

Volume conduction: activity from one source recorded by multiple electrodes [Holsheimer & Feenstra, 1977]

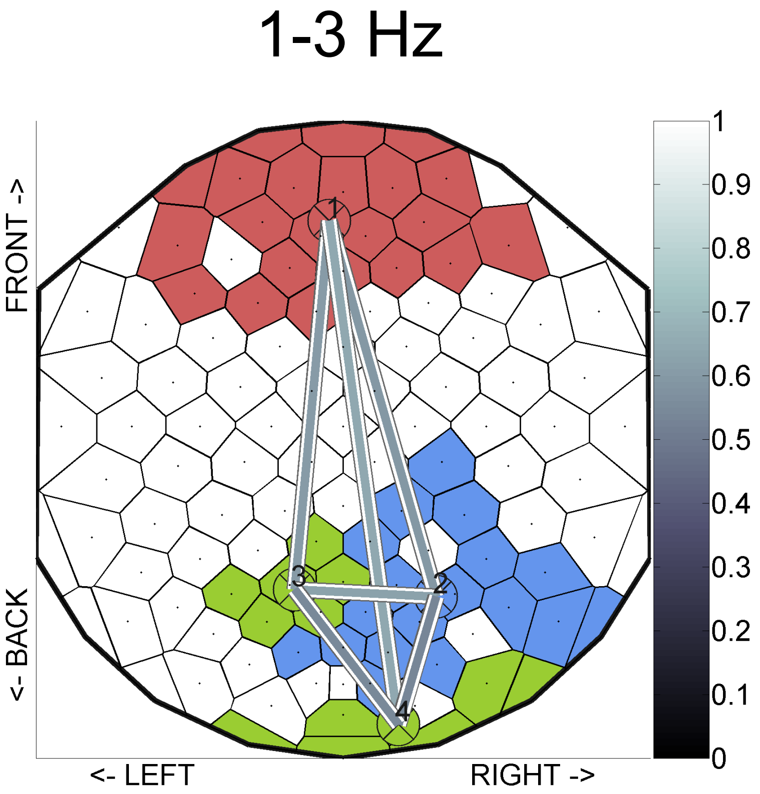
Functional Unit Maps

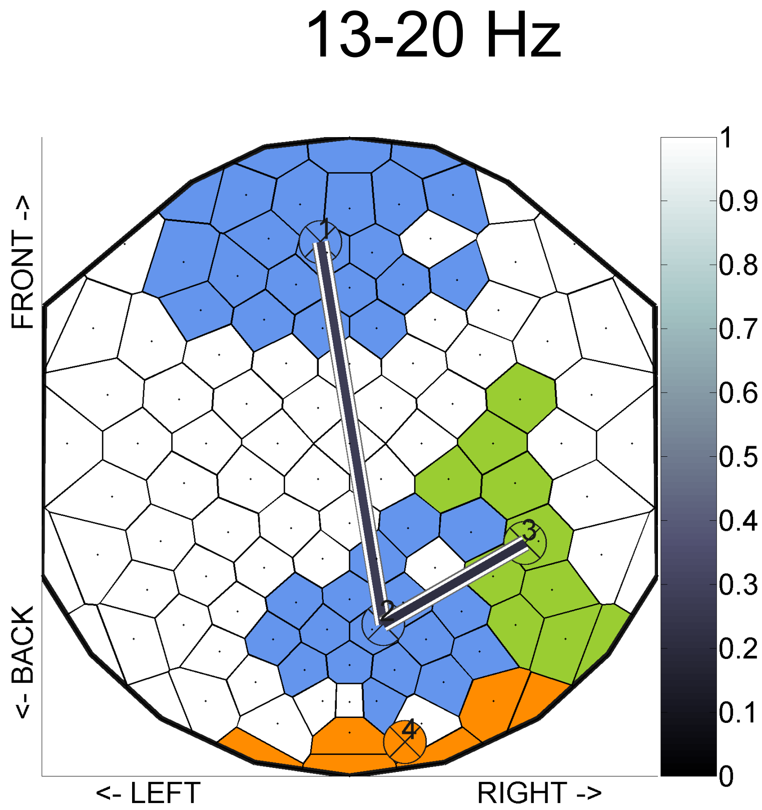
a. Calculate average coherence *S* between FUs
b. Lines connect FUs if *S* > *significance threshold*
c. Color mapped to value *S*



1-3Hz

Functional Unit Map



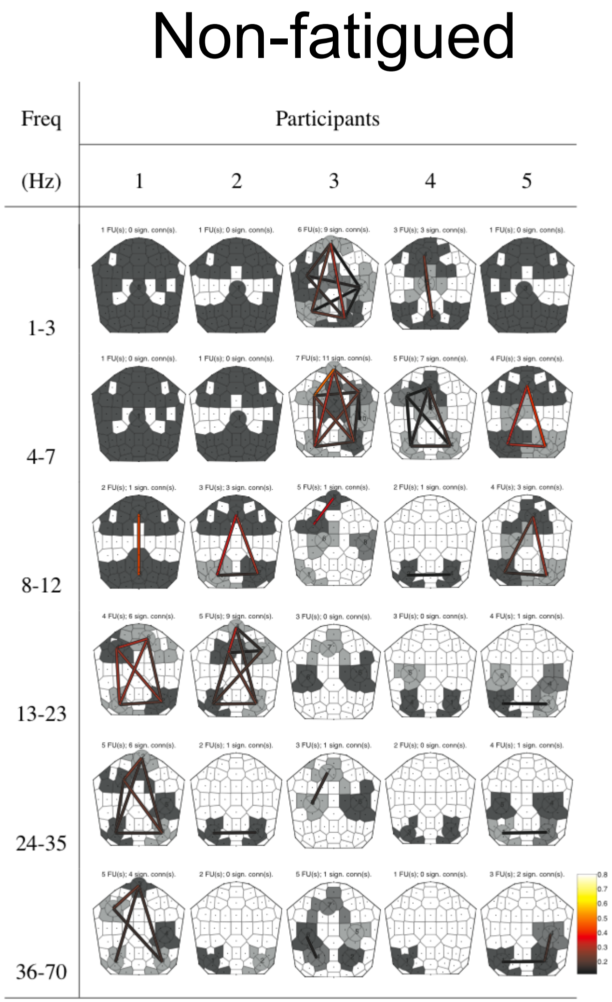


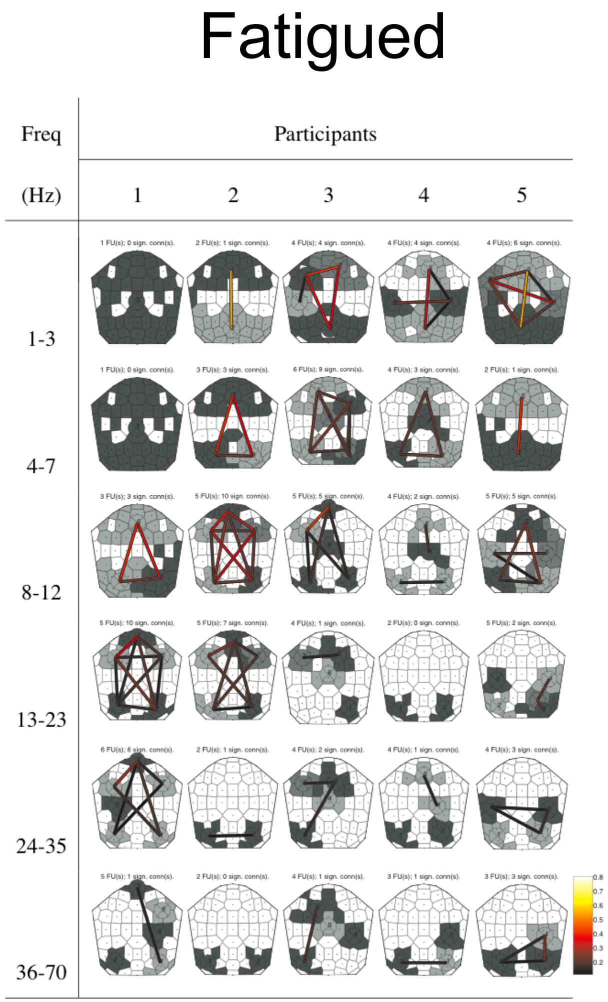
Simultaneous activity [Nunez et al, Electroenceph Clin Neurophysiol, 1997]
- at a more global scale for a lower EEG frequency
- at a more local scale for a higher EEG frequency

Similarly, we observe less connections for higher frequency

Application: Mental Fatigue

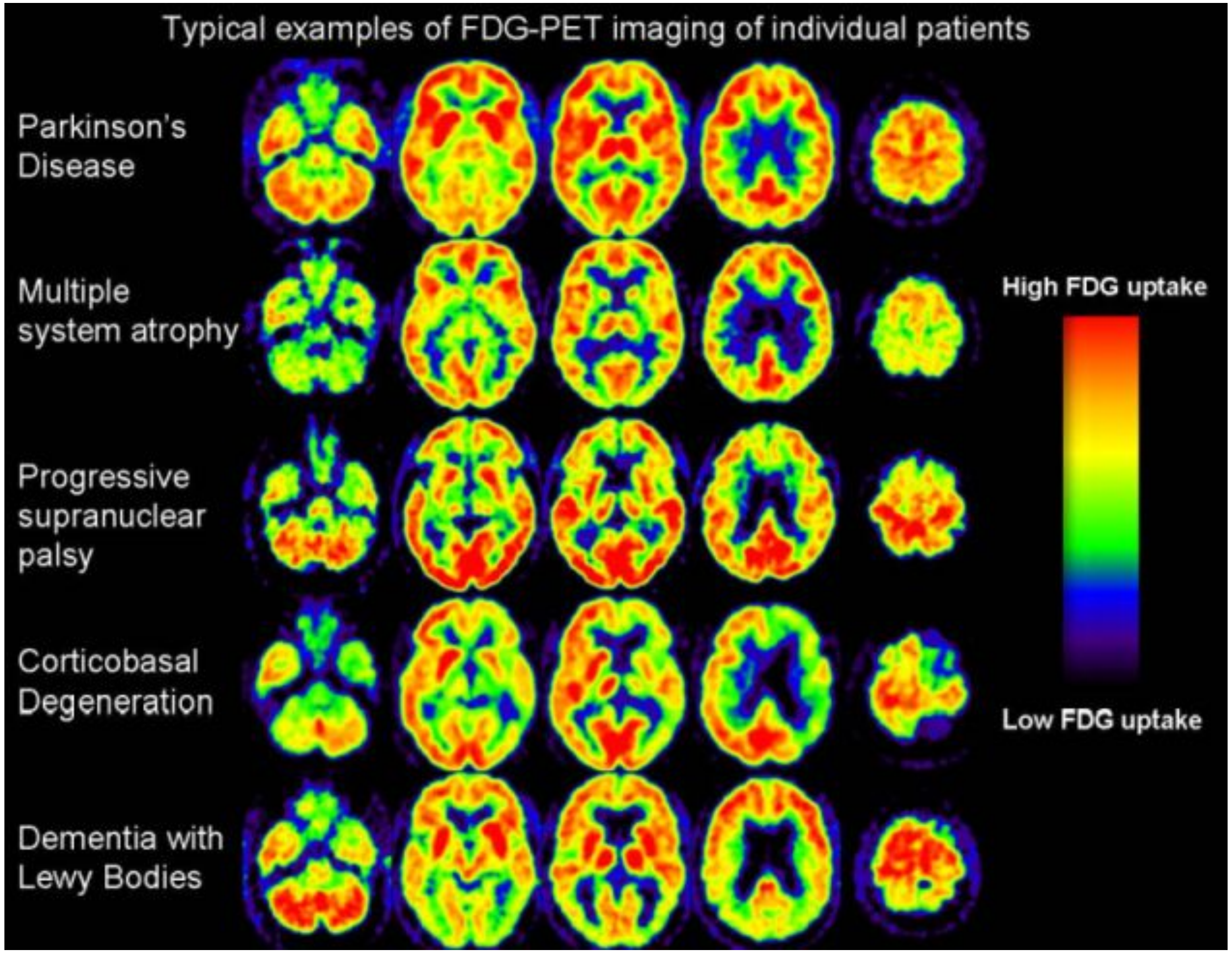
university of groningen





Lorist, Bezdan, ten Caat, Span, Roerdink and Maurits: Brain Research 1270, 95-106, 2009

FDG-PET Imaging of parkinsonisms



[18F]-fluorodeoxyglucose (FDG) positron emission tomography (PET)

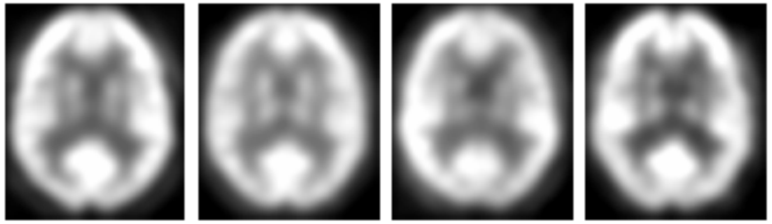
Mathematical classification model

university of groningen

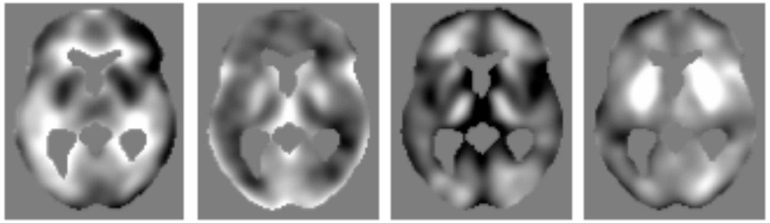
- Principal Component Analysis (PCA) and Scaled Subprofile Model (SSM)
- Extract disease-specific FDG-PET patterns (group-invariant subprofiles) for PD, MSA, PSP, etc.
- Subject score for each pattern measures how strongly this pattern is expressed in the subject
- Decision tree classification (C4.5, Quinlan 1993)

D Eidelberg, Trends in Neurosciences 32(10), 548 - 557, 2009
PG Spetsieris, Y Ma, v Dhawan, D Eidelberg, NeuroImage 45(4), 1241 - 1252, 2009

PCA and subject scores



(a) Preprocessed FDG-PET scans.

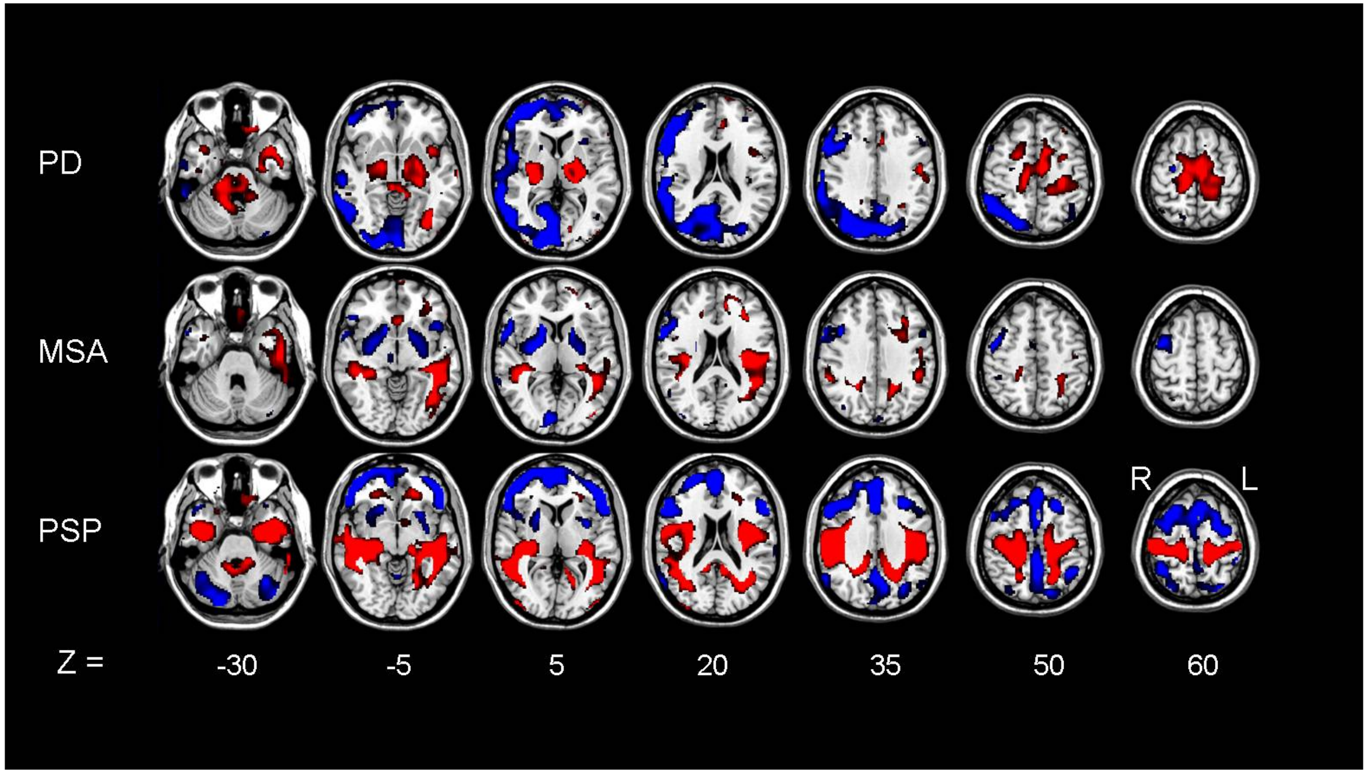


(b) The first four component images.

	PC1	PC2	PC3	PC4	...	Class
Scan 1	-625	826	-1164	149	...	HC
Scan 2	186	1395	135	207	...	HC
Scan 3	1273	-1420	-1070	947	...	MSA
Scan 4	-1331	-159	887	-1501	...	MSA
Scan 5	...	...	...	...	...	...
Scan 6	...	...	...	...	...	...
...	...	...	...	...	...	...

(c) Subject scores are computed as the projection of each scan onto each principal component image.

Combined GIS patterns



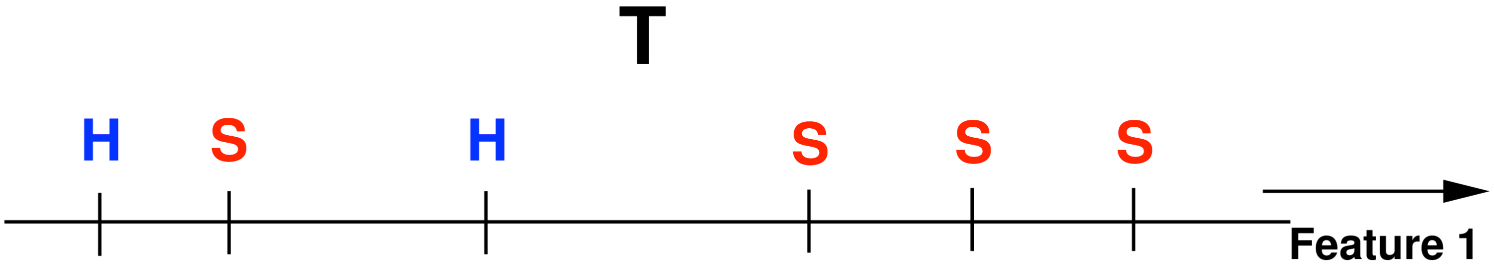
(T) maps of metabolic brain patterns overlaid on a T1 MR template. Relative metabolic decreases (blue) and increases (red) compared to the control group, thresholded at T= 3,7-6,7 (*P*< 0.001).

LK Teune, RJ Renken, D Mudali, BM De Jong, RA Dierckx, JBTM Roerdink, KL Leenders: Validation of parkinsonian disease-related metabolic brain patterns. Movement Disorders 2013, 28(4), 547-551

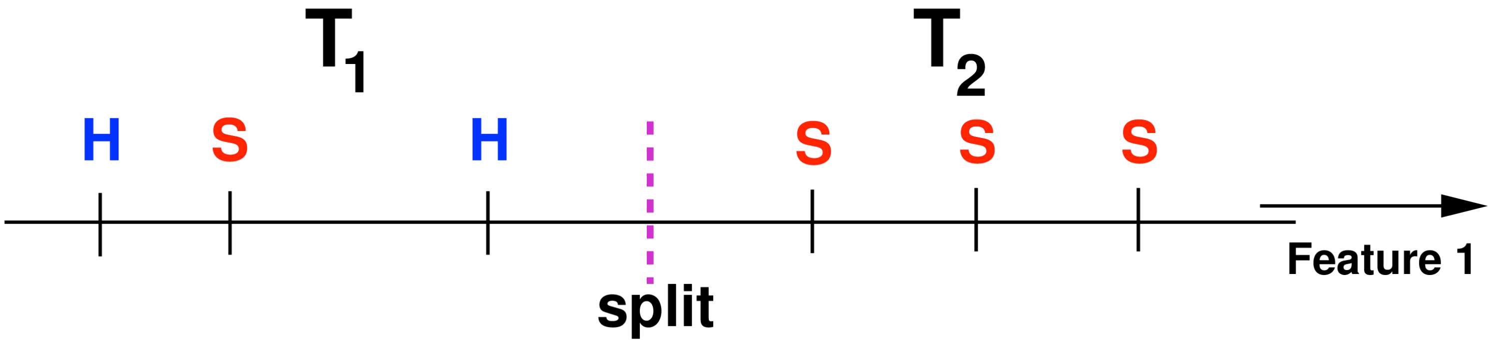
Decision tree classification

- Build a classifier from a set of training samples with a list of features (or attributes) and a class label
- Split a set of training samples into subsets so that the data in each of the subsets are "purer" than in the parent subset (based on information theory)
- The split is based on feature values only
- Result is a tree in which each leaf carries a class name and each interior node specifies a test on a particular feature
- The tree can now be used to classify unseen cases where the class label is unknown

How to split the data: information gain



$$info(T) = -\left(\tfrac{2}{6}\log_2(\tfrac{2}{6}) + \tfrac{4}{6}\log_2(\tfrac{4}{6})\right) = 0.92$$

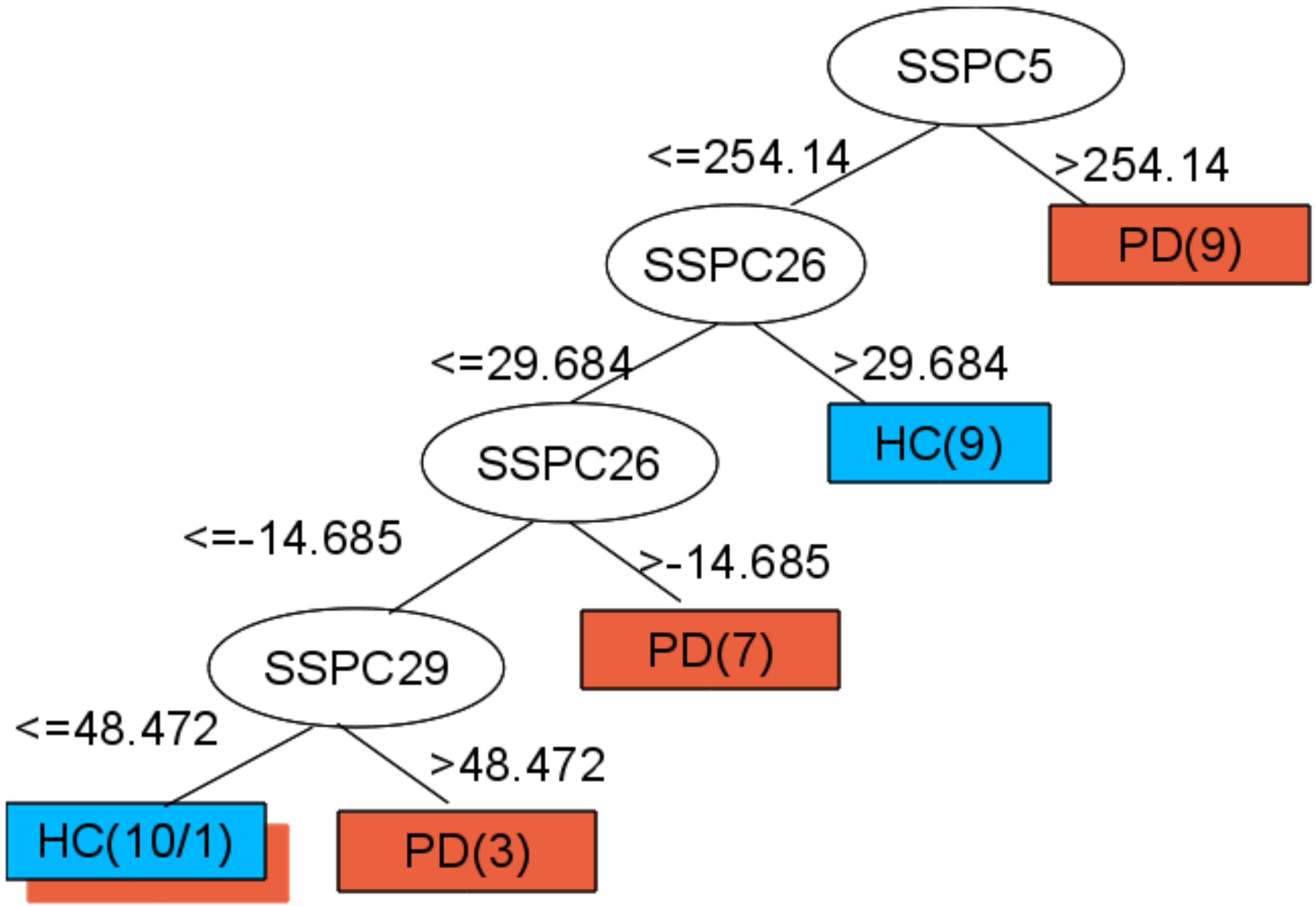


$$info(T_1) = 0.92 \qquad info(T_2) = 0$$

$$info_X(T) = \tfrac{3}{6}info(T_1) + \tfrac{3}{6}info(T_2) = 0.46$$

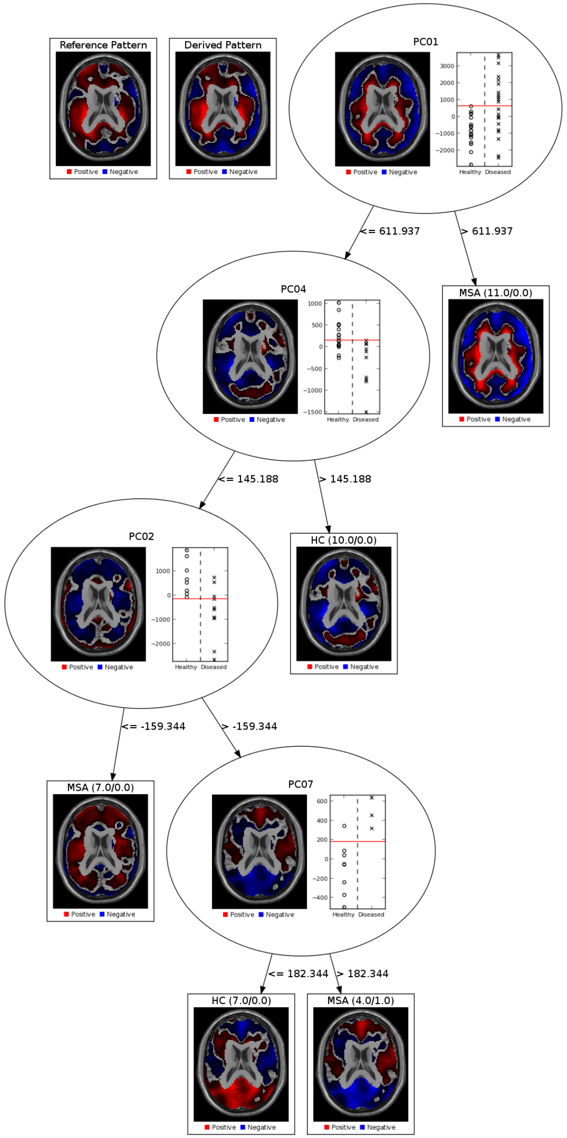
$$\boxed{gain(X) = 0.46}$$

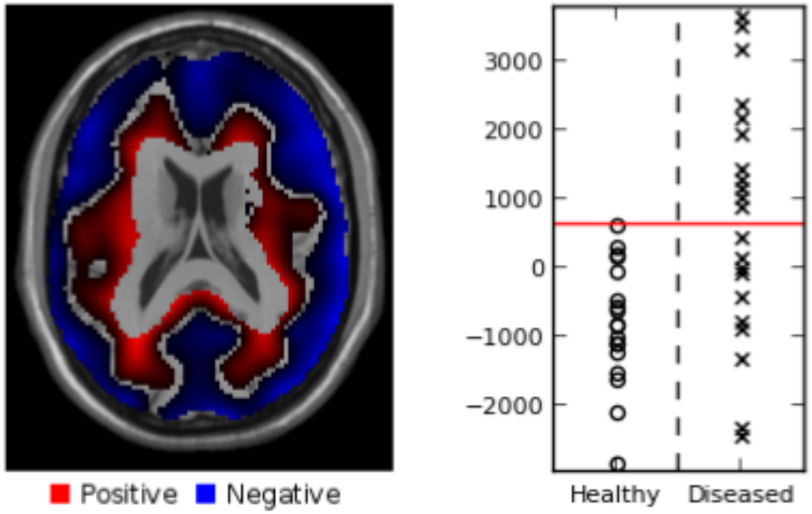
PD group vs healthy controls (HC)



20 PD patients, 18 healthy controls

Enhanced decision tree diagrams





e-Visualization of Big Data

Comp. Science

Astronomy

Center Inform Techn

- Target: very large data archives (petabyte range)
- Query driven visualization - Visual Analytics
- Medical imaging, astronomy, 3D electron microscopy
- Collaborative environments (touch displays, Infoversum)

Conclusions

- Large variety of brain imaging techniques, high costs
- Large range of spatial and temporal scales
- Extensive data processing chains: different techniques, many (hidden) parameters, implicit model assumptions
- Software tools: Large variety (sparsely documented)
- Biological variation: need image databases over collections of imaging conditions, people, populations; need probabilistic brain models
- Interaction between people from very diverse backgrounds needed