

# Aging - cognition, brain imaging and genetics

Multimodal MRI recordings, image processing, and data analysis

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*Visual Computing Forum*

<http://www.ii.uib.no/vis/vcf>

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# OUTLINE

- **Multimodal MRI**

= *Collection of MRI recordings obtained with different MR measurement techniques from the same subject - in the same imaging session*

- Structural 3D MRI (sMRI)
- Diffusion tensor imaging (DTI)
- Functional BOLD MRI (fMRI) in the resting state
  - ↑ *Blood Oxygen Level Dependent contrast*

- **Image processing workflows**

- Brain morphometry (FreeSurfer)
- White matter integrity and fiber tracking (Diffusion Toolkit & TrackVis)
- Resting state networks (the FC0N1000 scripts)

- **Longitudinal data analysis**

- Linear mixed models (R: lmer in the lme4 package)
- Nonlinear mixed effects estimation (MATLAB: nlmefit)

- **Data organization**

# The multimodal MRI protocol Wave1<sub>2005</sub>, Wave2<sub>2008/9</sub>, Wave3<sub>2011/12</sub>

1.5 T GE Signa Excite MRI scanner with a standard 8 chn receive only head coil:

Series		Pulse sequence parameters	W1	W2	W3
1	Localizer 2D	TR/TE = 7.8[ms]/1.7[ms]/30[°]; acq.voxel: 1.0×1.0×5.0 [mm <sup>3</sup> ]; 3 [imgs]	x	x	x
2	Ax PD/T2 2D FSE	TR/TE <sub>1</sub> /TE <sub>2</sub> /FA = 3840/12.1/84.9/90; voxel: 0.94×0.94×4.0; 52	x		
3	Sag T1 3D FSPGR IR preped	TR/TE/TI/FA = 9.45/2.41/450/7; voxel: 0.94×0.94×1.40; 124	x		
4	Sag T1 3D FSPGR IR preped	[ same as 3 to improve SNR for FreeSurfer segmentation ]	x		
5	Sag T1 3D FSPGR IR preped	TR/TE/TI/FA = 9.12/1.77/450/7; voxel: 0.94×0.94×1.40; 124			
6	Sag T1 3D FSPGR IR preped	[ same as 5 to improve SNR for FreeSurfer segmentation ]			
7	Ax DTI, EP SE, 26 slices	TR/TE/FA = 7900/97.1/90; 25 b=1000, 5 b=0; voxel: 0.94×0.94×4.0; 780	x		
8	Ax DTI, EP SE, 25 slices	TR/TE/FA = 7900/104.8/90; 25 b=1000, 5 b=0; voxel: 0.94×0.94×4.0; 750		x	
9	Ax DTI, EP SE, 25 slices	TR/TE/FA = 7900/110.5/90; 25 b=1000, 5 b=0; voxel: 0.94×0.94×4.0; 750			x
10	Ax fMRI GRE EPI Resting	TR/TE/FA=2000/50/90; voxel: 3.75×3.75×5.5; 25 slices; 256 volumes; 6400		x	x
11	Ax fMRI GRE EPI Fingertap	TR/TE/FA=3000/50/90; voxel: 3.75×3.75×5.5; 25 slices; 120 volumes; 3000		x	x
12	Ax GRE Haemoseries	TR/TE <sub>1</sub> /TE <sub>2</sub> /FA=540/15/67/20; voxel: 0.94×0.94×4.0; 25 slices; 50			x

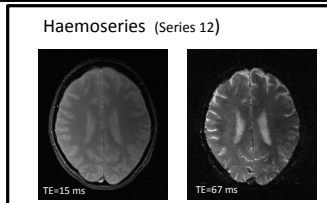
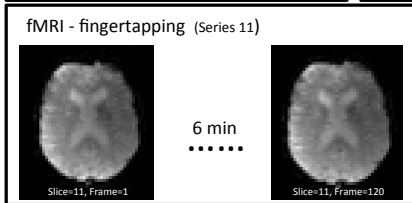
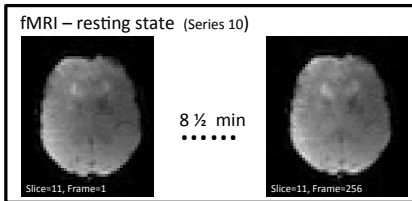
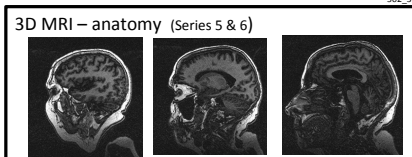
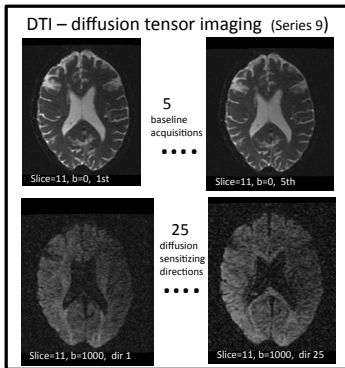
FSE=Fast spin-echo; FSPGR=Fast spoiled gradient-echo; EP SE=Echo-planar spin-echo; GRE EPI=Gradient-echo echo-planar; IR=Inversion recovery.

- Image acquisitions being analysed in the project<sup>1</sup>:
  - Structural 3D Anatomy - 2 × 124 images / subject / wave (series 5 & 6)
  - Diffusion tensor imaging - 750 images / subject / wave (series 9)
  - Resting state fMRI - 6400 images / subject / wave (series 10)

<sup>1</sup>Up until now ...

# An example of multimodal MRI recordings

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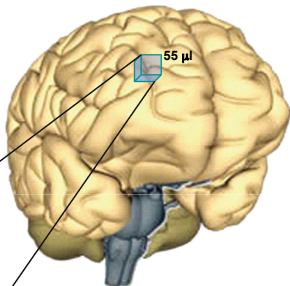




# Voxels and their constituents in brain MRI

## Scales:

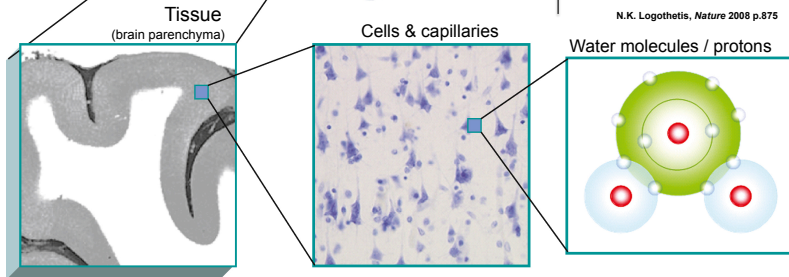
- Microscopic
- **Mesoscopic** [mm] [s]
- Macroscopic



\* Given these neuro-statistical data, what are the actual contents of a neuroimaging voxel? An examination of the 300 top-cited cognitive fMRI studies suggests that the commonly used in-plane resolution is 9–16 mm<sup>2</sup>, for slice thicknesses of 5–7 mm. The average voxel size before any pre-processing of the data is thus 55 μl (or 55 mm<sup>3</sup>). Often the effective size is 2–3 times larger due to the spatial filtering that most investigators apply to improve the functional SNR. Less than 3% of this volume is occupied by vessels and the rest by neural elements.

A typical fMRI voxel of 55 μl in size thus contains **5.5 million neurons**, **2.2–5.5 x 10<sup>10</sup> synapses**, **22 km of dendrites** and **220 km of axons**. \* !!

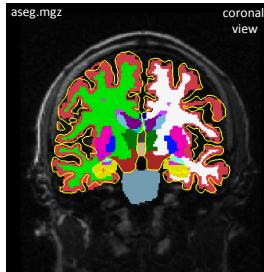
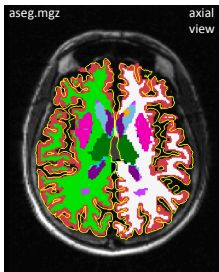
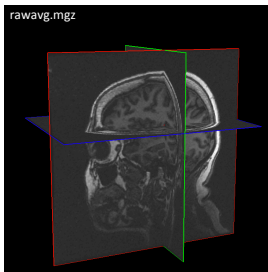
N.K. Logothetis, *Nature* 2008 p.875



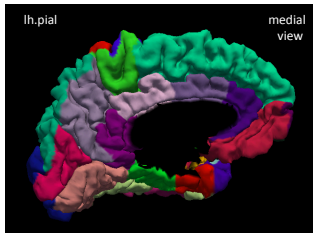
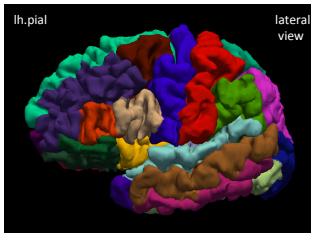
From Baars & Gage: *Cognition, Brain, and Consciousness* (2010)

# Image processing workflows - FreeSurfer

## Brain segmentation:



## Brain surface reconstruction and cortical parcellation:



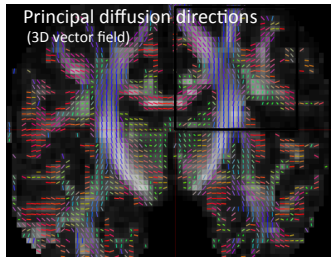
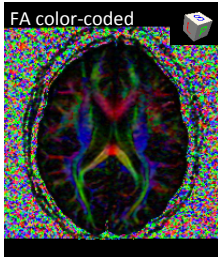
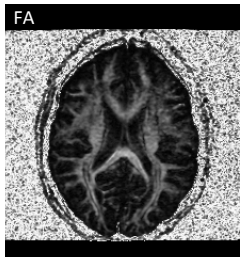
FreeSurferColorLUT

0	Unknown
1	Left-Cerebral-Exterior
2	Left-Cerebral-White-Matter
3	Left-Cerebral-Cortex
4	Left-Lateral-Ventricle
5	Left-Inf-Lat-Vent
6	Left-Cerebellum-Exterior
7	Left-Cerebellum-White-Matter
8	Left-Cerebellum-Cortex
9	Left-Thalamus
10	Left-Thalamus-Proper
11	Left-Caudate
12	Left-Putamen
13	Left-Pallidum
14	3rd-Ventricle
15	4th-Ventricle
16	Brain-Stem
17	Left-Hippocampus
18	Left-Amygdala
19	Left-Insula
20	Left-Operculum
21	Line-1
22	Line-2
23	Line-3
24	CSF
25	Right-Caudate

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FreeSurfer 5.1 & Freeview

# Image processing workflows - Diffusion Toolkit



From: Are Losnegård, In prep.

The diffusion tensor:

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

Eigen decomposition:

$$\begin{aligned} D \mathbf{\varepsilon}_1 &= \lambda_1 \mathbf{\varepsilon}_1 \\ D \mathbf{\varepsilon}_2 &= \lambda_2 \mathbf{\varepsilon}_2 \\ D \mathbf{\varepsilon}_3 &= \lambda_3 \mathbf{\varepsilon}_3 \end{aligned}$$

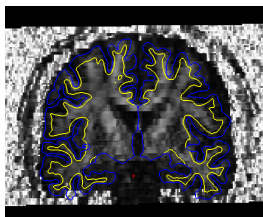
$$\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$$

Principal diffusion direction:  $\mathbf{\varepsilon}_1 = (\varepsilon_{1x}, \varepsilon_{1y}, \varepsilon_{1z})$

Fractional anisotropy ("white matter integrity"):

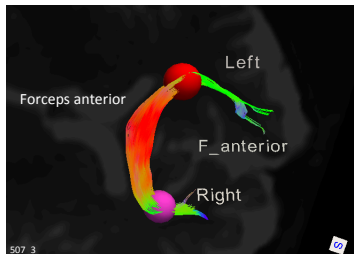
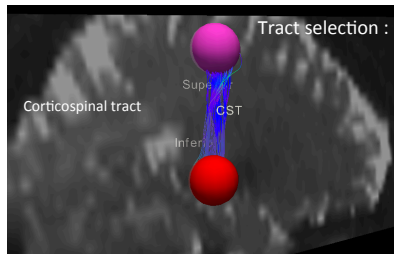
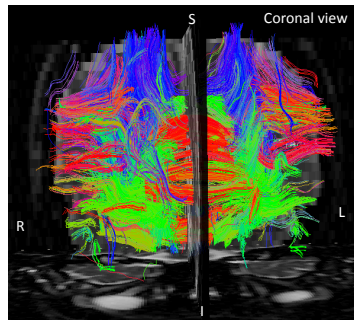
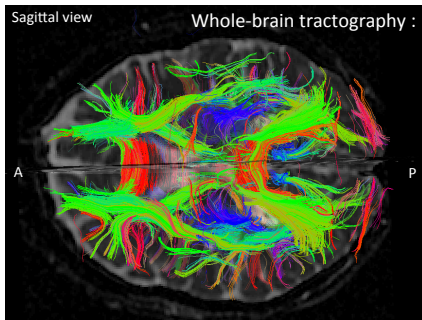
$$FA = \sqrt{\frac{1}{2} \frac{\sqrt{(\lambda_1 - \lambda_2)^2 + (\lambda_1 - \lambda_3)^2 + (\lambda_2 - \lambda_3)^2}}{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}} \quad 0 \leq FA \leq 1$$

Checking goodness of co-registration  
between Anatomy and DTI (FA)



aging\_anatomy\_dti\_integration\_centos\_macos\_al20130228.m

# Image processing workflows - TrackVis



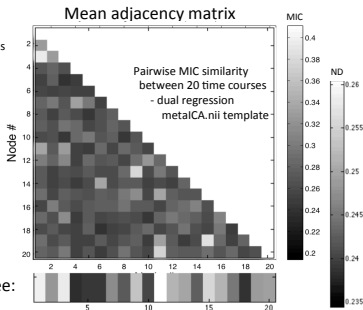
# Image processing workflows - FC0N1000 scripts

## Graph analysis of resting state functional connectivity:

(Eikeland et al, HBM 2013)

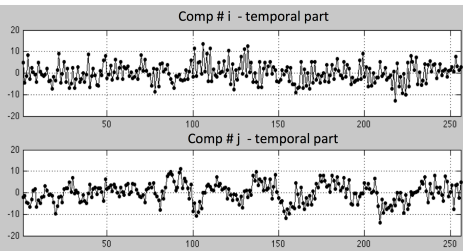
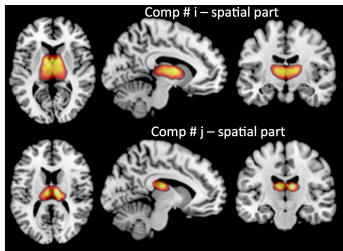
Wave 2 & 3: 80 subjects

MIC =  
Maximal  
Information  
Coefficient  
(Reshef et al, 2011)



Name
0_preprocess.sh
1_anatpreproc.sh
2_funcpreproc.sh
3_registration.sh
4_segment.sh
5_nuisance.sh
6_singlesubjectRSFC.sh
7_singlesubjectALFF.sh
8_singlesubjectDR.sh
batch_list.txt
batch_process.sh
example_seed_list.txt
Fox_seed_list.txt
▶ seeds
▶ templates
▶ tissuespriors

[http://www.nitrc.org/plugins/mwiki/index.php/fcon\\_1000:ScriptUse](http://www.nitrc.org/plugins/mwiki/index.php/fcon_1000:ScriptUse)



## Longitudinal data analysis (LDA) - Linear mixed-effect models

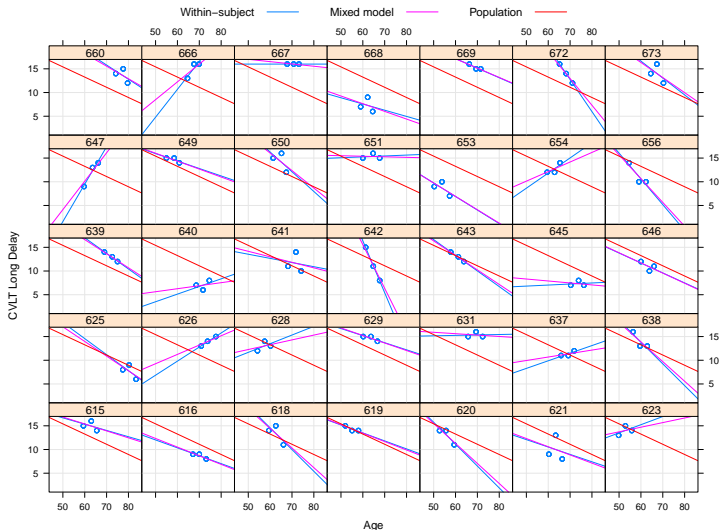
Let  $y_{ij}$  denote the response at the  $j$ th observation of the  $i$ th subject;  $i = 1, \dots, N$ ,  $j = 1, \dots, n_i$ , and  $x_{ij}$  be the corresponding value of the explanatory (covariate) variable  $x$ , then the standard linear mixed-effects model with random intercept  $b_{0i}$  and random slope  $b_{1i}$  is:

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + (b_{0i} + b_{1i} x_{ij}) + \epsilon_{ij}$$

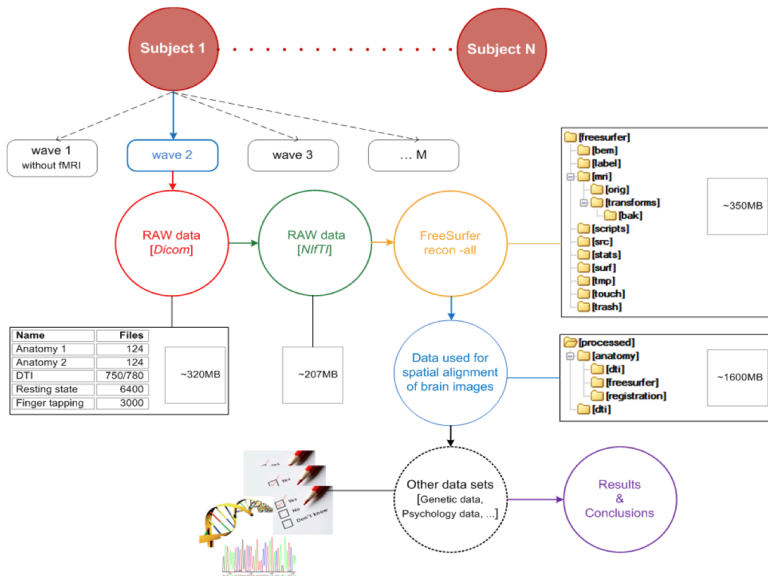
- the  $\beta_k$ s are fixed effect parameters
- the  $b_{ki}$ s are random effect parameters
- $\epsilon_{ij}$  is the error for observation  $j$  in subject  $i$ , where the errors for subject  $i$  are assumed to be multivariate normally distributed

## CVLT LongDelay - fit a linear mixed-effect model

Age<sub>ij</sub> as a predictor for  $y_{ij} = \text{LongDelay}_{ij}$  across subjects  $i = 1, \dots, 106$  and waves  $j = 1, 2, 3$ :  $y_{ij} = \beta_0 + \beta_1 \text{Age}_{ij} + (b_{0i} + b_{1i} \text{Age}_{ij}) + \epsilon_{ij}$  (CVLT\_analysis\_long\_al20130213.R)



# Data organisation (SVN/MySQL - Sebastian Bablock, 2009)





# Thanks !

UiB project members  
and collaborators:

Erlend Hodneland	<b>Biomed/math</b> , post doc
Martin Ystad	<b>Biomed</b> , MD, PhD
Steinunn Adolfsdottir	<b>IBMP</b> , PhD student
Judit Haasz	<b>Biomed</b> , MD PhD student
Erling Tjelta Westlye	<b>Biomed</b> , MD PhD student
Alexandra Vik	<b>IBMP</b> , PhD
Rune Eikeland	<b>IBMP</b> , PhD
Erik Hanson	<b>Math</b> , PhD
Martin Andersson	<b>IBMP</b> , PhD
Jonn-Terje Geitung	<b>Radiology</b> , HDS
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Eike Wehling	<b>IBMP</b> , post doc
Are Losnegård	<b>Biomed</b> , PhD student
Ivar Reinvang	<b>UiO</b>
Thomas Espeseth	<b>UiO / IBMP</b>
Tessa Welte	<b>Tu/E, Eindhoven, Netherlands</b>
Clément de Ribet	<b>ISIMA, Blaise Pascal University, FR</b>
MedViz	<b>UiB / HUS / CMR</b>
The Vis Group	<b>UiB / Informatics</b>

UiB VISAPIC component of PPMIC 3  
[www.neuroinformatics-imageanalysis.org](http://www.neuroinformatics-imageanalysis.org)