Deep learning for medical imaging

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Master 2 - MVA

Course website: http://www.aramislab.fr/teaching/DLMI-2019-2020/
Piazza (for registered students):
https://piazza.com/centralesupelec/spring2020/mvadlmi/

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Part 1 – Introduction
1.1 Introduction
1.1.1 What is medical imaging?

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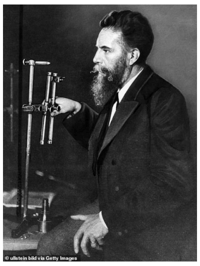
What is medical imaging?

Techniques that allow to **see** (*study*) **inside the human body** in vivo and **non-invasively**



First X-ray radiography (1895) - Wilhelm Röntgen (Nobel Prize in Physics, 1901)

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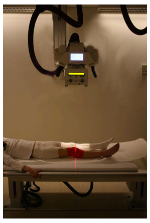
Medical imaging today

Multiple machines

X-ray radiography



MRI

PET / CT

Ultrasound (echography)

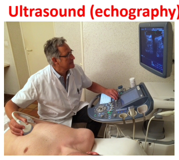


Image sources: http://radiologie-abbeville.fr/files/Echographie%20g%C3%A9n%C3%A9rale.jpg, CENIR (ICM), https://fr.wikipedia.org/wiki/Tomographie_par_%C3%A9mission_de_positons, https://en.wikipedia.org/wiki/Radiography

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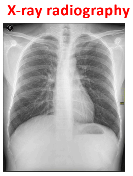
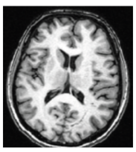
Medical imaging today

Multiple types of images

X-ray radiography



MRI



Ultrasound

PET

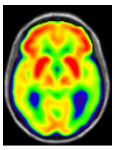


Image sources: https://fr.wikipedia.org/wiki/Radiographie, https://en.wikipedia.org/wiki/Obstetric_ultrasonography, Burgos et al, 2017 https://hal.inria.fr/hal-01567343

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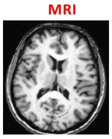
Medical imaging today

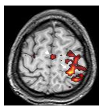
Multiple types of images
with the same machine (MRI)

Anatomical MRI

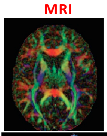


Angiography

Functional MRI



Diffusion MRI



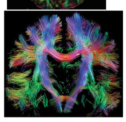


Image sources: https://en.wikipedia.org/wiki/Magnetic_resonance_angiography, Mukerjee et al, Tournier et al

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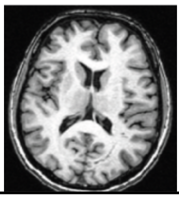
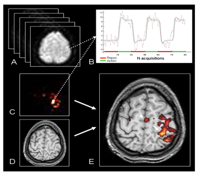
What is medical imaging?

Not only **see inside the human body**

But also **study multiple phenomena** which are inaccessible to the naked eye
- Metabolism
- Oxygenation of the blood
- Molecular structure





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Part 1 – Introduction
1.1 Introduction
1.1.2 What is medical imaging used for?

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What is medical imaging used for?

Medical care

- Detect lesions / anomalies
  - Find the cause of a set of symptoms

MRI

65-year old female

Presenting with left-side weakness and headache

Glioblastoma (brain tumour)

Source: https://radiopaedia.org/cases/glioblastoma-nos-13?lang=us

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What is medical imaging used for?

Medical care

- Screening

Mammography

56-year old female

Routine screening
Asymptomatic

Potential breast tumour
(refered for biopsy)

Source: https://radiopaedia.org/cases/small-breast-cancer?lang=us

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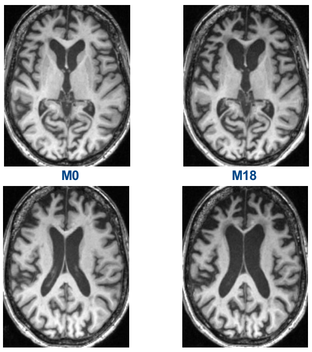
What is medical imaging used for?

Medical care

- Follow up a pathology

Patient with neurodegenerative disease

(followed over 18 months)



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What is medical imaging used for?

Medical care

- Quantify (extract biomarkers)
  - For instance, segmentation for volumetric analysis
    - Reduced volume of specific brain structures: iomarker of neurodegenerative diseases
    - Enlarged volume of the left ventricle of the heart

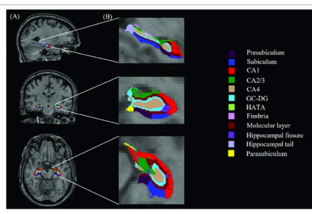

Image source: Zheng et al, The Volume of Hippocampal Subfields in Relation to Decline of Memory Recall Across the Adult Lifespan, 2018

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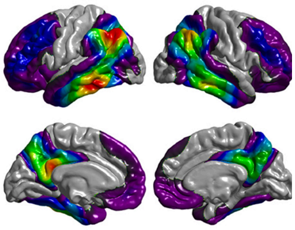
What is medical imaging used for?

Research

- Clinical research
  - Understand the alterations produced by a given disease

Brain alterations associated with Alzheimer's disease



Brain areas with significantly reduced metabolism in patients with Alzheimer's disease compared to healthy controls, as studied with PET imaging

Source: Marcoux et al, Front Neuroinformatics, 2018

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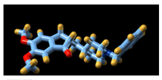
What is medical imaging used for?

Research

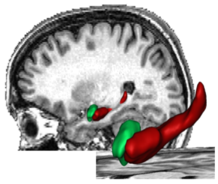
- Clinical research
  - Evaluate the effect of a treatment

Studying the effect of a treatment (donepezil) on the volume of the hippocampus in Alzheimer's disease



- Double-blind, randomized, placebo-controlled

Hippocampal atrophy was reduced by 45% in one year with donepezil compared to placebo



Source: Dubois et al, Alzheimer's and dementia, 2015

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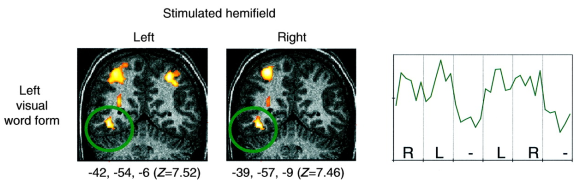
What is medical imaging used for?

Research

- Basic research
  - Cognitive neuroscience

Studying which parts of the brain are used for reading



Source: Cohen et al, The visual word form area: Spatial and temporal characterization of an initial stage of reading in normal subjects and posterior split-brain patients, Brain, 2000

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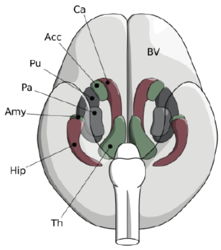
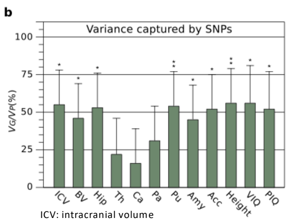
What is medical imaging used for?

Research

- Basic research
  - Genetics and neuroscience

Heritability of the size of brain structures





Source: Toro et al, Genomic architecture of human neuroanatomical diversity, Molecular Psychiatry, 2015

ICV: intracranial volume
BV: brain volume
VIQ: verbal IQ
PIQ: performance IQ

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Part 1 – Introduction
1.1 Introduction
1.1.3 Medical image computing

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Medical image computing

Scientific field dedicated to the computational analysis of medical images

At the cross-road of

- Computer vision / image processing
- Machine learning
- Statistics
- Geometry

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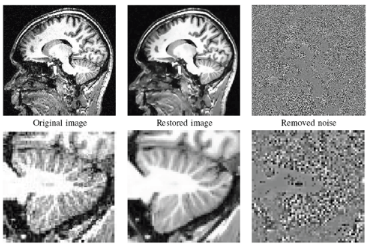
Medical image computing – what for?

- Enhance medical images
  - Denoising



Hellier, TMI 2008

Denoising of brain MRI

Provide higher quality images to the radiologist

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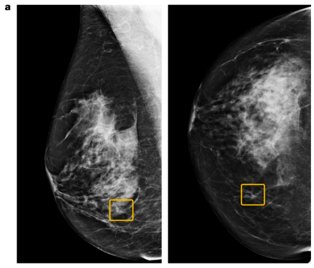
Medical image computing – what for?

- Assist medical evaluation
  - Detection
  - Diagnostic classification



Source: McKinney et al International evaluation of an AI system for breast cancer screening, Nature, 2020

Automatic detection of breast cancer in mammography images

Reduce reading time for the radiologist

In the future: screen automatically and aks the radiologist only for difficult cases?

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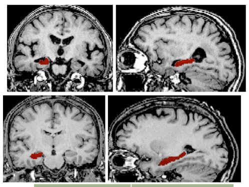
Medical image computing – what for?

- Quantify
  - Segmentation



	Alzheimer vs controls
Volume reduction	-32%
Sensitivity	84%
Specificity	84%

Automatic segmentation of the hippocampus in Alzheimer's disease

Enrich visual evaluation with quantitative measures

Source: Colliot et al, 2008

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Medical image computing – what for?

- Predict
  - Predict the future state of the patient

Predict the future occurrence of Alzheimer's disease (within 3 years)

Classifier - Features	Bal. acc.	AUC	Acc.	Sens.	Spec.
SVM - T1w MRI	0.670	0.736	0.698	0.586	0.754
SVM (trained on CN $A\beta$- vs AD $A\beta$+) - T1w MRI	0.679	0.764	0.708	0.547	0.811
SVM - FDG PET	0.708	0.777	0.732	0.633	0.782
SVM (trained on CN $A\beta$- vs AD $A\beta$+) - FDG PET	**0.761**	**0.818**	**0.788**	0.666	0.856
RF - $\text{Clinical}_{\text{base}}$ + Score $_{\text{T1}}$	0.717	0.792	0.732	0.671	0.763
RF - $\text{Clinical}_{\text{base}}$ + Score $_{\text{FDG}}$	0.760	0.831	0.791	0.669	0.852
RF - $\text{Clinical}_{\text{base}}$ + Scores $_{\text{T1,FDG}}$	0.769	0.855	0.796	0.685	0.852
RF - $\text{Clinical}_{\text{base}}$ + RAVLT + Scores $_{\text{T1,FDG}}$	**0.791**	0.881	0.809	0.735	0.846
RF - $\text{Clinical}_{\text{base}}$ + ADAS + Scores $_{\text{T1,FDG}}$	**0.790**	0.873	0.810	0.729	0.851
RF - $\text{Clinical}_{\text{base}}$ + RAVLT + ADAS + Scores $_{\text{T1,FDG}}$	**0.792**	0.888	0.811	0.736	0.849

$\text{Clinical}_{\text{base}}$: gender, education level, MMSE score, sum of boxes of CDR test

Source: Samper-Gonzalez et al, 2019

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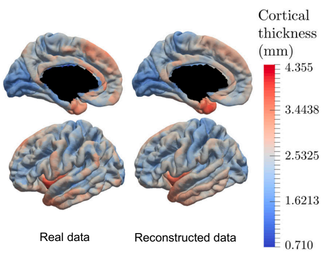
Medical image computing – what for?

- Predict
  - Predict the future observations



Real data

Reconstructed data

Predict the future MRI data in patients with Alzheimer's disease

Source: Koval et al, Front Neurosci, 2019

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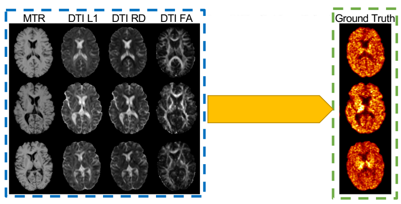
Medical image computing – what for?

- Synthesis of medical imaging data



Synthesize PET imaging from MRI imaging

Source: Wei et al, Medical Image Analysis, 2019

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Part 1 – Introduction
1.1 Introduction
1.1.4 Specificities of medical image computing

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Specificities of medical image computing

Why it is not only computer vision applied to medical images

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Specificities of medical image computing

- 3D
  - Most medical images are 3D

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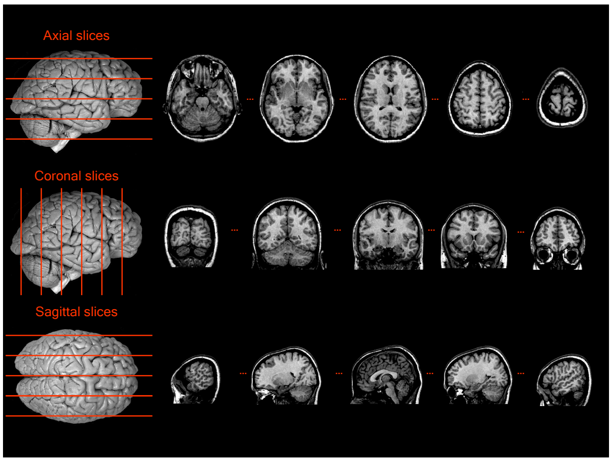

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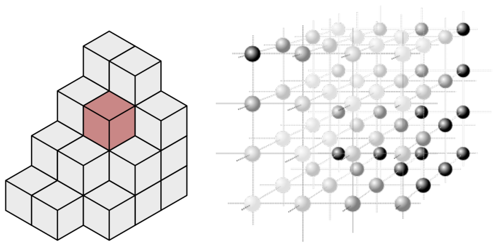
Specificities of medical image computing

- 3D
  - Most medical images are 3D



Voxel=volume element

Image source: https://en.wikipedia.org/wiki/Voxel

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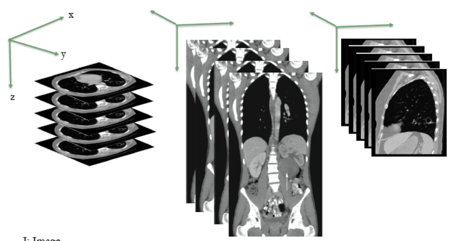
Specificities of medical image computing

- 3D
  - Most medical images are 3D



I: Image
I(x,y,z) denotes intensity value at pixel location x,y,z
Note also that whatever you see on the left is right part of the body!

Image source: http://www.cs.ucf.edu/~bagci/teaching/mic17.html

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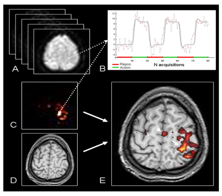
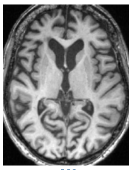
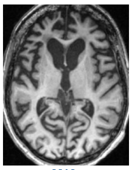
Specificities of medical image computing

- Temporal phenomena
  - Across multiple time scales



Second





Year

Functional brain images, cardiac images…

Longitudinal studies

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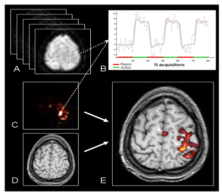
Specificities of medical image computing

- Multiple phenomena and image types



Anatomical vs functional

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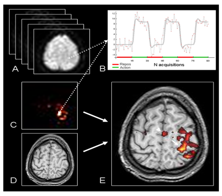
Specificities of medical image computing

- Multiple phenomena and image types



Time-series

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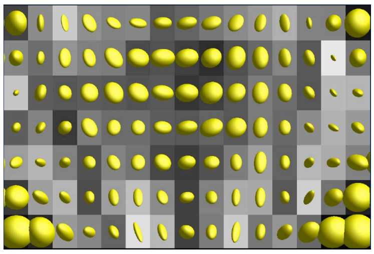
Specificities of medical image computing

- Multiple phenomena and image types



Tensor images

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Specificities of medical image computing

- Validation
  - Critical
  - Can be difficult to perform
- Clinical relevance
  - Need close collaboration with physicians to identify relevant problems
- Multidisciplinary collaboration
  - Find a common language

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Medical image computing with deep learning

- Has achieved impressive results, as in other fields (CV, NLP…)
  - Even though there are some inherent difficulties, in particular the small sample size
- Is not a universal solution
  - Other methods may remain competitive for some applications

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Part 1 – Introduction
1.1 Introduction
1.1.5 About this course

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Course content

- Content:
  - theoretical and practical aspects of deep learning for medical imaging
  - covers the main tasks involved in medical image analysis (classification, segmentation, registration, generative models…)
  - state-of-the-art deep learning techniques are presented, alongside some more traditional image processing and machine learning approaches
- Learning objectives
  - have knowledge of state-of-the-art deep learning techniques for medical imaging
  - have a deeper understanding of deep learning methods, applicable not only to medical images but also other types of data
  - know how to build and validate deep learning models for medical images

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Sessions

1	Medical image acquisition techniques Main medical image analysis tasks	3H CM	O. Colliot
2	Classification	1h30 CM + 1h30 TP	O. Colliot / E. Thibeau-Sutre
3	Detection	1h30 CM + 1h30 TP	M. Vakalopoulou
4	Segmentation	1h30 CM + 1h30 TP	M. Vakalopoulou
5	Registration	3h CM	M. Vakalopoulou
6	Denoising and reconstruction	1h30 CM + 1h30 TP	M. Vakalopoulou
7	Generative models (autoencoders, GANs)	3h CM	O. Colliot
8	Validation, interpretation and reproducibility	3h CM	O. Colliot

Course website: http://www.aramislab.fr/teaching/DLMI-2019-2020/
Piazza (for registered students): https://piazza.com/centralesupelec/spring2020/mvadlmi/

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Course content

- Note: today's course will be very different from the others
  - Presentation of medical image acquisition techniques
    - Closer to physics than machine learning

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Part 1 - Introduction
1.2 Main medical imaging modalities

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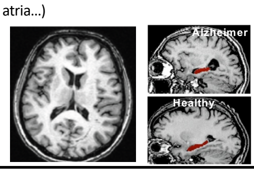
Two main types of medical images

Structural images

Also called morphological or anatomical

Visualize the structures

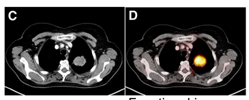
- Differentiate between tissues (e.g. skin, bone, muscle, fat…)
- Between organs (heart, brain…)
- Between anatomical structures within an organ (e.g. in the heart: ventricles, atria…)



Functional images

Provide information about a functional process

- Metabolism (e.g. glucose consumption)
- Blood flow
- …



Anatomical image | Functional image (showing malignant lung tumour) superimposed on anatomical image

http://www.snmmi.org/Patients/Procedures/Content.aspx?ItemNumber=13526&navItemNumber=13230

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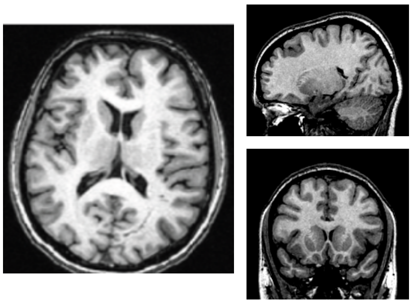
Two main types of medical images

Structural images



Brain MRI

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Two main types of medical images

Structural images

Whole Body CT

https://www.siemens-healthineers.com/en-sg/computed-tomography/news/mso-imaging-a-tale-of-two-cities.html

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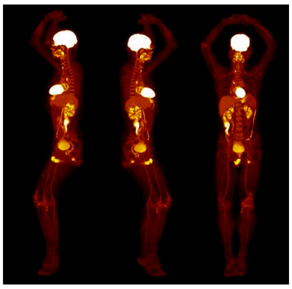
Two main types of medical images

Functional images



Whole Body PET

https://www.nature.com/articles/d41586-019-01833-z

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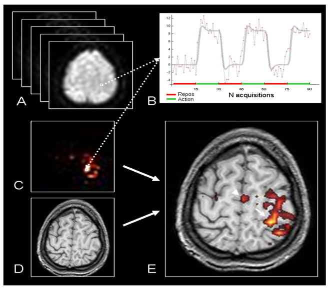
Two main types of medical images

Functional images



Functional MRI: right hand activation

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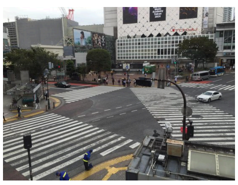
Two main types of medical images

Structural images



https://media-cdn.tripadvisor.com/media/photo-s/06/bd/47/14/shibuya-crossing-almost.jpg

Functional images

https://www.videezy.com/transportation/39282-ho-chi-minh-city-traffic-at-intersection-vietnam

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Part 1 - Introduction
1.2.1 Structural imaging
1.2.1.1 X-ray radiography

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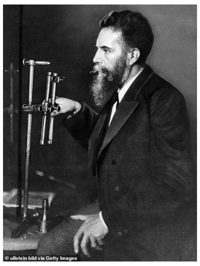
X-Ray radiography



First X-ray radiography (1895) - Wilhelm Röntgen (Nobel Prize in Physics, 1901)

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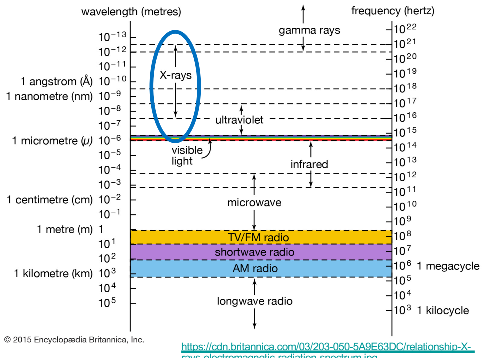
X-Ray radiography



https://cdn.britannica.com/03/203-050-5A9E63DC/relationship-X-rays-electromagnetic-radiation-spectrum.jpg

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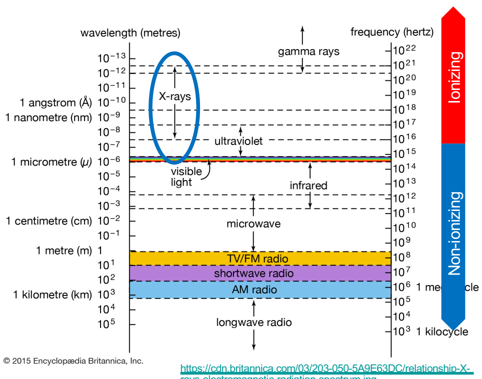
X-Ray radiography

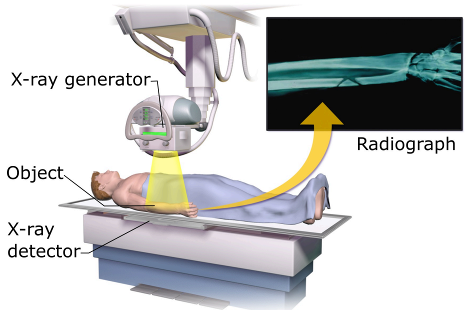


https://cdn.britannica.com/03/203-050-5A9E63DC/relationship-X-rays-electromagnetic-radiation-spectrum.jpg

51

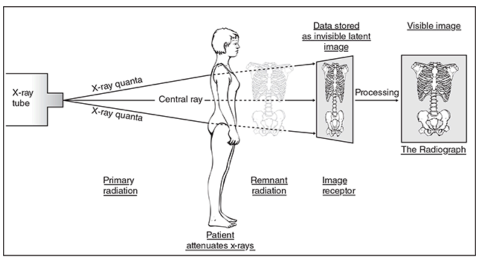
X-Ray radiography

Projectional radiography



52

X-Ray radiography



Source: Lynn N. McKinnis: *Fundamentals of Musculoskeletal Imaging*, 4th Edition: www.FADavisPTCollection.com Copyright © F. A. Davis Company. All rights reserved.

X-rays are absorbed by heavy atoms and not by lighter atoms

Bones: high absorbtion

Soft tissues: lower absorbtion

Air: no absorbtion

53

X-Ray radiography

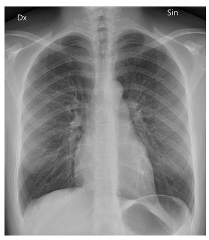


Image source:
https://en.wikipedia.org/wiki/Dental_radiography
https://en.wikipedia.org/wiki/Chest_radiograph

X-rays are absorbed by heavy atoms and not by lighter atoms

Bones: high absorbtion

Soft tissues: lower absorbtion

Air: no absorbtion

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Part 1 - Introduction
1.2.1 Structural imaging
1.2.1.2 CT

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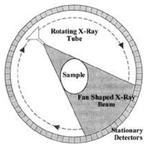
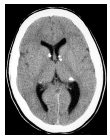
CT

CT: Computed Tomography

Principle : 3D reconstruction from multiple radiographic projections





Good visualization of bone

High resolution

Poor visualization of soft tissues (in particular in the brain)

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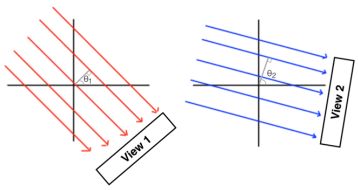
CT

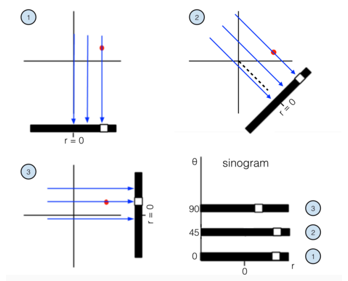


Multiple CT views, each made up of parallel rays incident from a different angle. Theta defines the angle of incidence.

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

57

CT



Sinogram formation from individual projection angles

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

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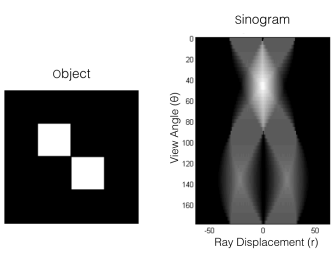
CT



Sinogram of an example object

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

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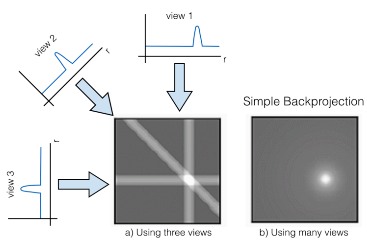
CT

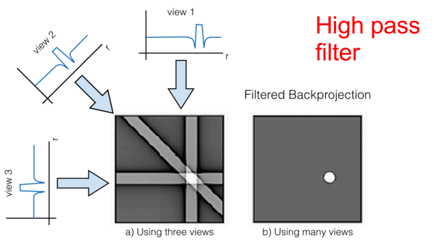


Backprojection. Each view (intensity vs. radius) is stretched backwards in the same direction as the ray and superimposed. Here, three views are used to illustrate the technique (a), and the final result is shown (b).

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

60

CT



Filtered Backprojection. Each view (intensity vs. radius) is filtered and then stretched backwards in the same direction as the ray. Here, three views are used to illustrate the technique (a), and the final result is shown (b).

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

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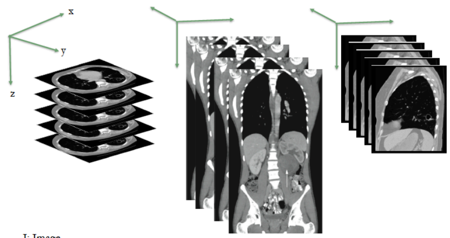
CT



I: Image
I(x,y,z) denotes intensity value at pixel location x,y,z
Note also that whatever you see on the left is right part of the body!

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Part 1 - Introduction
1.2.1 Structural imaging
1.2.1.3 Structural MRI

63

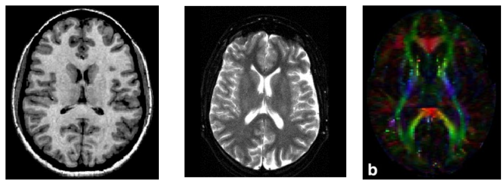
MRI – Magnetic resonance imaging

High spatial resolution (millimeter), 3D

Acceptable temporal resolution (second) – for functional imaging

Very versatile modality (multiple types of images, multiple phenomena)

Not radiation



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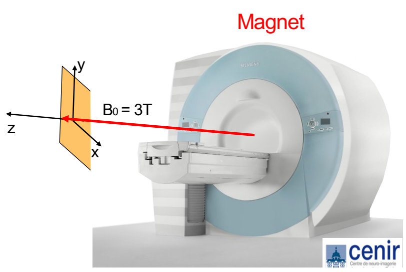
MRI



MRI Siemens Magnetom Trio/TIM of the CENIR
Centre for neuroimaging research, Paris

65

MRI

The signal

- It depends on the physico-chemical organization of water within tissues (mobility, chemical liaisons)
- It is produced through excitation at a specific frequency (resonance) and recorded at the return at equilibrium (relaxation)
- It is located in space through additional magnetic fields (field gradients)

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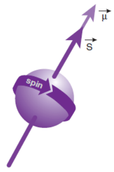
MRI

The signal

- It is directly related to
  - The magnetic moment of hydrogen nuclei (protons) that are within tissues (in particular, water)
  - To their properties within an external magnetic field B_0



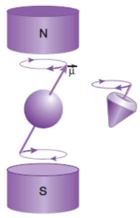
From (Kastler and Vetter)

67

MRI

- The magnetic moment µ of each proton placed into a static magnetic field B_0
  - orients itself (parallel/anti-parallel)
  - describe a movement of precession at the following angular speed (Larmor relationship)

$$\omega_0 = \gamma . B_0$$



Where B_0 is the external (static) magnetic field and gamma is the gyromagnetic ratio (specific to each nucleus, here protons)

From (Kastler and Vetter)

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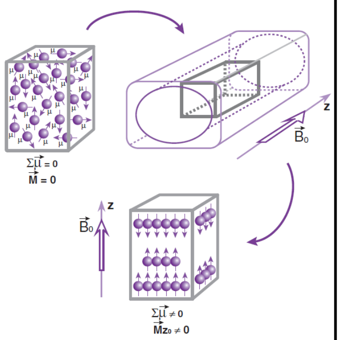
MRI

The sum of magnetic moments µ of all protons is oriented along B_0



From (Kastler and Vetter)

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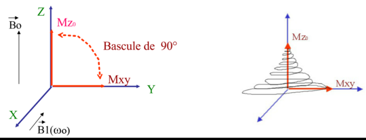
MRI

Excitation/relaxation

- Excitation by a coil which creates a magnetic field B1 orthogonal to B0
  - B1 is a rotating magnetic field with frequency ω0 (in order to create resonance)
- Rotation of M0 around the direction B1 (resonance). Creation of a component Mxy
- Return to equilibrium: relaxation -> production of the MR signal



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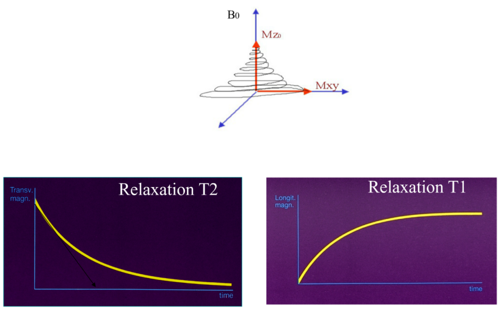
MRI



Décroissance de Mxy **Repousse de Mz**

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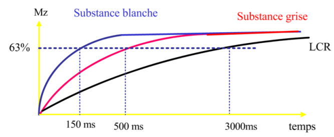
MRI

Relaxation T1



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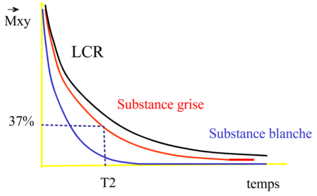
MRI

Relaxation T2



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MRI

Obtaining an image

- Spatial coding (x,y,z) relies on the use of magnetic field gradients (Gx, Gy, Gz), with the same direction as B0 but which amplitude varies linearly along directions x, y et z
- It allows to "control" the frequencies of precession at each point, as a function of the magnetic field in this point

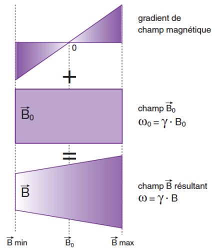

Fig. 6-3. Le gradient de champ magnétique se superpose au champ magnétique principal $\vec{B}_0$, les modifications de champ produites se rajoutant ou se retranchant de $\vec{B}_0$.
Le champ résultant B croit linéairement dans la direction du gradient (centré par rapport à $\vec{B}_0$). Par conséquent, la fréquence de Larmor croit aussi de manière linéaire, proportionnellement au champ résultant B : on a maintenant $\omega = \gamma \cdot B$. *Schéma : J.-P. Dillenseger.*

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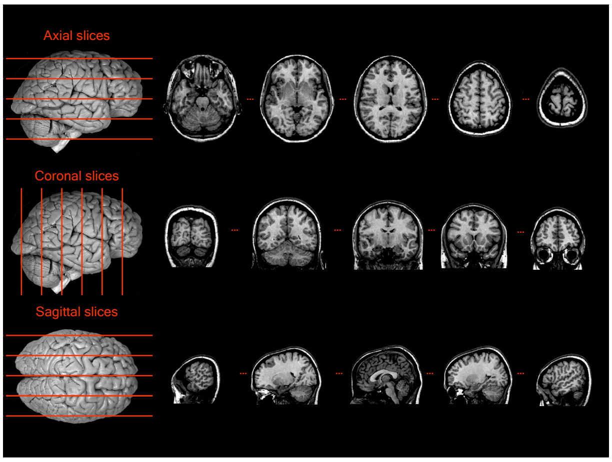

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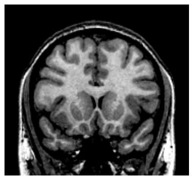
Anatomical MRI

T1-weighted MRI
Resolution ~ 1mm x 1mm x1mm



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Diffusion MRI

- Brownian motion
- Allow to study the structure of tissues at the microscopic level (cell membranes, fibers…)
- In the brain: allows studying the white matter connections
- Other applications: heart, muscle…

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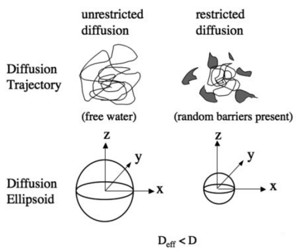
Diffusion MRI



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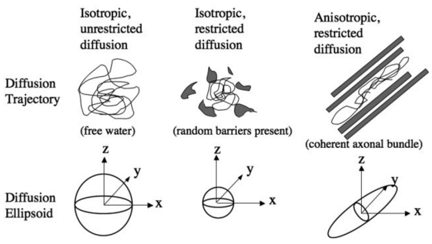
Diffusion MRI



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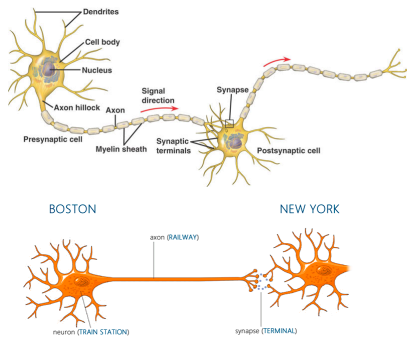
Neurons and axons



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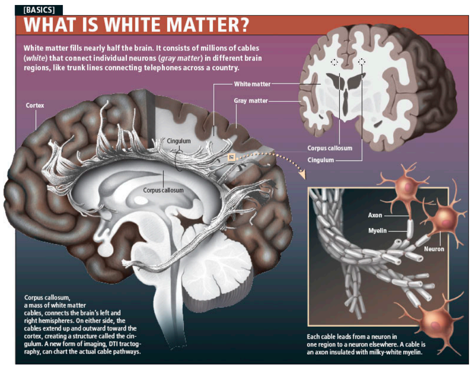
White matter



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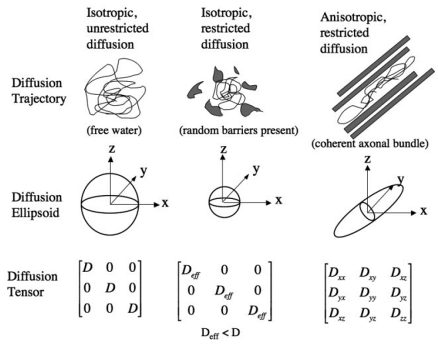
Diffusion MRI



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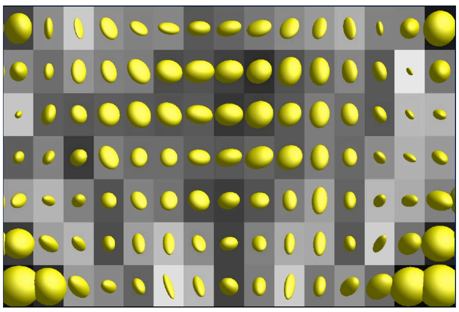
Diffusion MRI



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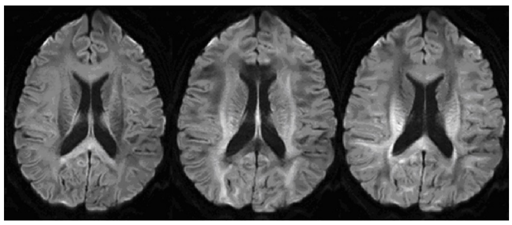
Diffusion MRI

Gradient direction



DWI z DWI x DWI y

(From Cauchi and Yamamoto)

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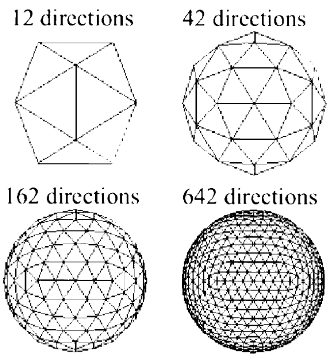
Diffusion MRI



(From Le Bihan et al, 2002)

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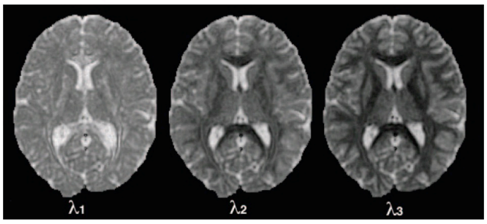
Diffusion MRI

$$\begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{bmatrix} \Rightarrow \Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} = R \cdot D \cdot R^T.$$



(From Mukerjee et al, 2008)

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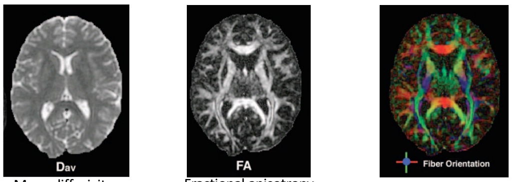
Diffusion MRI

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} = R \cdot D \cdot R^T.$$



Mean diffusivity

Fractional anisotropy

$$D_{av} = \frac{\lambda_1+\lambda_2+\lambda_3}{3} = \text{trace}(D)/3 \qquad FA = \frac{\sqrt{(\lambda_1-\lambda_2)^2+(\lambda_2-\lambda_3)^2+(\lambda_3-\lambda_1)^2}}{\sqrt{2}\sqrt{\lambda_1^2+\lambda_2^2+\lambda_3^2}}$$

(From Mukerjee et al, 2008)

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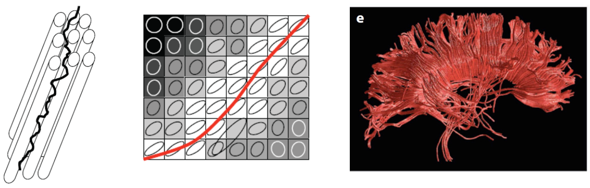
Tractography

- Macroscopic estimate of the trajectories of white matter fiber bundles



(From Johansen-Berg et al, 2009)

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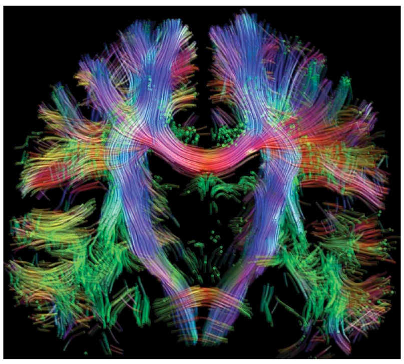
Diffusion MRI



(From Tournier et al, 2011)

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Part 1 - Introduction
1.2.2 Functional imaging
1.2.2.1 PET

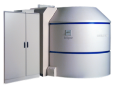
90

PET – Positron Emission Tomography

- 1970's
- Uses radioactive compounds which emitt positrons (produced by a cyclotron)
- Short radioactive half-life
- Many types of compounds → multiples functions can be explored
- Spatial resolution ≈ 5 mm
- Quantitative measure
- Expensive

PET

CT Scanner



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PET

- Intra-veinous injection of a vector, a molecule chosen for its interest regarding the phenomenon one aims to study
- Marked by a radioactive atom

VECTOR

ISOTOPE

^{18}F : T1/2 = 109 mn
^{11}C : T1/2 = 20 mn
^{15}O : T1/2 = 2 mn

92

PET

- Intra-veinous injection of a vector, a molecule chosen for its interest regarding the phenomenon one aims to study
- Marked by a radioactive atom

VECTOR

β+ (emission of a positron)

ISOTOPE

^{18}F : T1/2 = 109 mn
^{11}C : T1/2 = 20 mn
^{15}O : T1/2 = 2 mn

93

PET

- Intra-veinous injection of a vector, a molecule chosen for its interest regarding the phenomenon one aims to study
- Marked by a radioactive atom

VECTOR

β+

ISOTOPE

^{18}F : T1/2 = 109 mn
^{11}C : T1/2 = 20 mn
^{15}O : T1/2 = 2 mn

Annihilation with an electron of the environment

94

PET

- Intra-veinous injection of a vector, a molecule chosen for its interest regarding the phenomenon one aims to study
- Marked by a radioactive atom

VECTOR

β+ γ γ

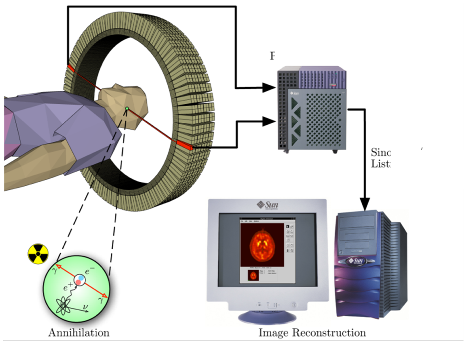
ISOTOPE

^{18}F : T1/2 = 109 mn
^{11}C : T1/2 = 20 mn
^{15}O : T1/2 = 2 mn

PET

95

PET



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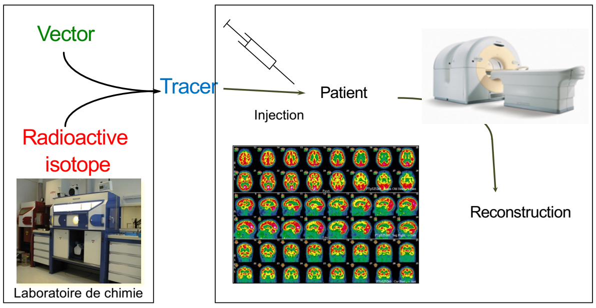
PET

Injection of a radioactive tracer → measures the number of disintegrations ↔ concentration of the tracer



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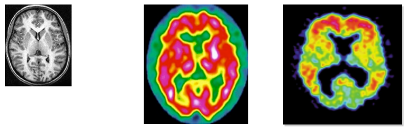
PET

Multiple uses depending on the tracer

- Study brain metabolism
- Studying neurotransmission, inflammation, amyloid plaques…



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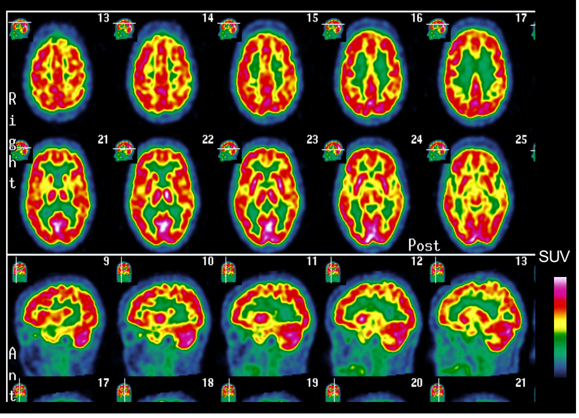
Normal brain FDG PET



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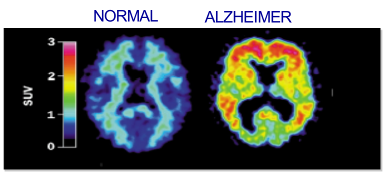
PET

Imaging amyloid plaques in Alzheimer's disease



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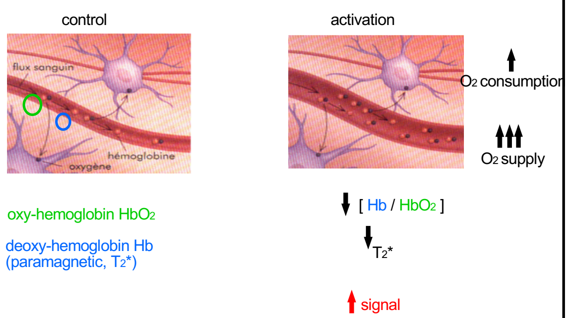
Part 1 - Introduction
1.2.2 Functional imaging
1.2.2.2 Functional MRI

101

Functional MRI

Direct measure of brain activity
BOLD (Blood Oxygen Level Dependent)



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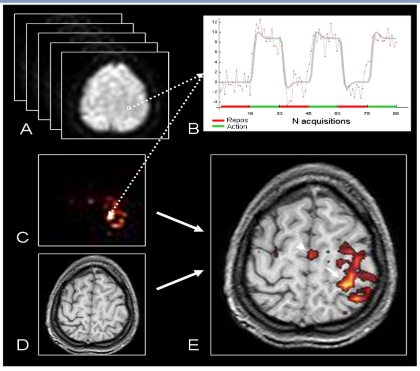
Functional MRI



Right hand motion

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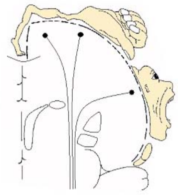
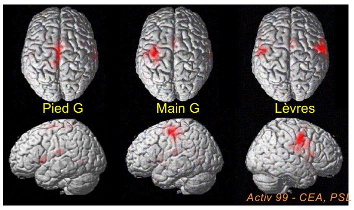
MRI

Motor activations

- Somatotopy





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MRI

Versatile technique

- Anatomical MRI: tissues and structures
- Diffusion MRI: connections, fibers
- Functional MRI: brain activity

Started a revolution in neuroscience

Application to multiple organs: brain, heat, knee…

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Part 1 - Introduction
1.2.2 Functional imaging
1.2.2.3 EEG/MEG

106

EEG/MEG

- Surface recording of brain activity
  - Electrical activity
    - Electro-encephalography - EEG
  - Magnetic activity
    - Magneto-encephalography - MEG

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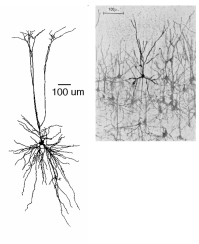
EEG / MEG

Neuronal electrophysiology

- Pyramidal neuron
  - Large cell
  - Organized in parallel in macro-assemblies
  - Superimposition of electrical currents
    - The result is detectable at the surface of the scalp



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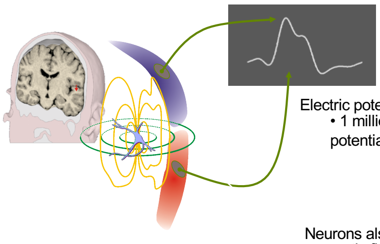
EEG / MEG



Electric potential
- 1 million de neurones created a potential of around 100µV

Neurons also produce magnetic fields
Magnetoencephalography (MEG)

109

EEG / MEG

Instrumentation: EEG

1945

1955

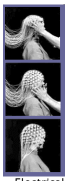
110

EEG / MEG

Instrumentation: EEG

- More sensors
  - Up to 256
- High temporal resolution
  - < 1 millisecond

MicroMed



Electrical Geodesics

NeuroScan

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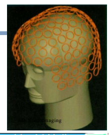
EEG / MEG

Instrumentation: MEG



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Part 1 - Introduction
1.3 Main tasks in medical image computing

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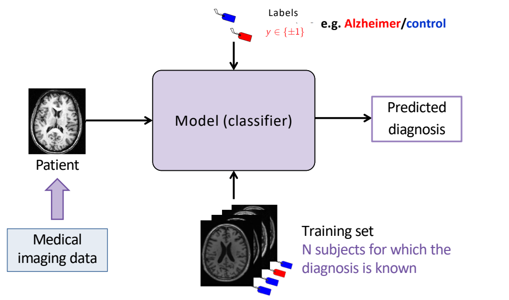
Classification – Diagnosis / Prognosis



Supervised learning

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Classification

Examples:
- Differential diagnosis of neurodegenerative diseases
  - Patient presenting with cognitive deficits, what is the underlying cause?
- Predicting the future clinical state
  - Patient presenting with subtle cognitive decline at baseline, will he have lost autonomy in 5 years ?

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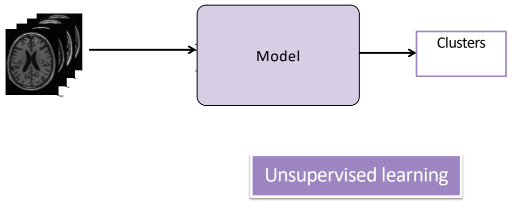
Clustering – Discover disease subtypes



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Clustering

- Different symptoms for a given biological cause
- Different biological causes for a given set of symptoms

⇨ Find homogeneous subtypes of diseases

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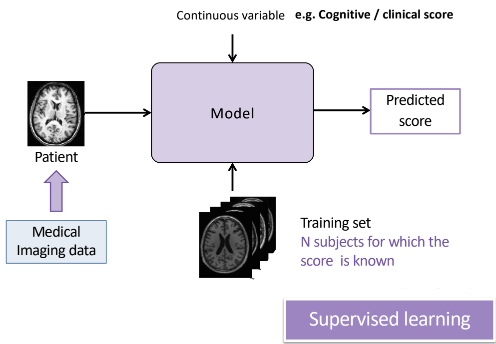
Regression – Predict clinical scores



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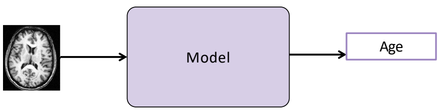
Regression

Example : predict age from brain MRI



	BLUP mean	SVM	6-layer CNN	ResNet	Inception V1	Ensemble prediction
MAE (SE)	5.32 (0.19)	5.31 (0.18)	4.18 (0.16)	4.02 (0.15)	3.82 (0.14)	3.46 (0.13)
|ρ|	0.32	0.58	0.25	0.24	0.41	0.32

(Couvy-Duchesne et al, In preparation)

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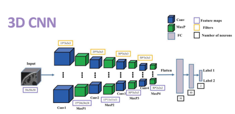
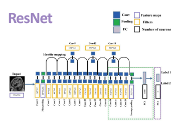
Classification / Regression – typical approaches

Typical approaches: 3D extensions of networks used for natural image classification





Alternatives: other classification/regression approaches with pre-extracted features
- SVM
- Random forests
- LASSO
- ...

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Detection

To do

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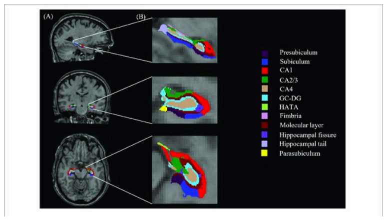
Segmentation

Delineate “objects” in images: tissues, anatomical structures, lesions…



Source: Zheng et al, The Volume of Hippocampal Subfields in Relation to Decline of Memory Recall Across the Adult Lifespan, 2018

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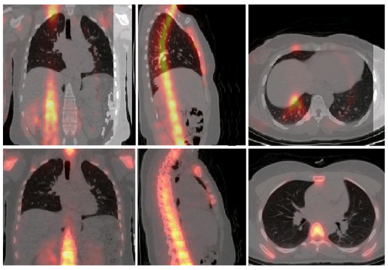
Registration

- Definition: put two images in spatial correspondence



[Source Tang et al]

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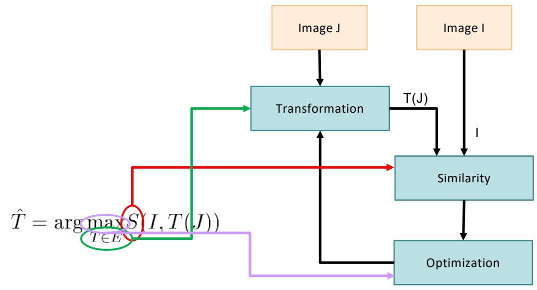
Registration

- Problem setting



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Registration

- Intra-subject, intra-modality
  - Deformation: in general rigid
  - Similarity: simple criterion (e.g. sum of square differences)

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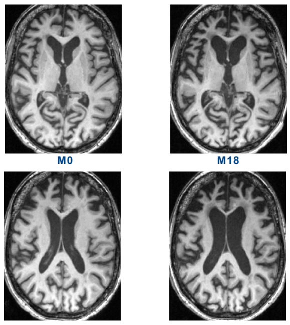
Registration

- Intra-subject, intra-modality, longitudinal
  - Deformation: non-linear

Same patient at different time points (e.g. 18 months after)



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Registration

- Intra-subject, inter-modality
  - Deformation: rigid, affine or non-linear
  - Similarity: complex criterion (e.g. mutual information)

Brain imaging

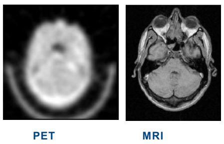

Image source: (Mangin, 1995)

Thoracico-abdominal imaging

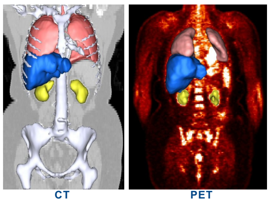

Image source (Camara et al,, 2007)

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Registration

- Inter-subject, intra-modality
  - Deformation: non-linear
    - Account for inter-individual variability

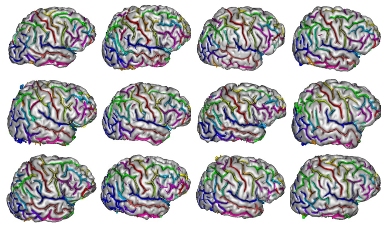

Image source: Mangin et al

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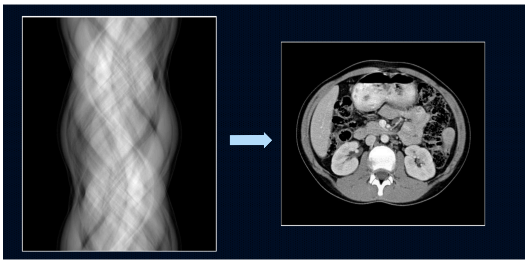
Image reconstruction



Source: https://de.medical.canon/wp-content/uploads/sites/17/2016/08/Metal-Artefact-Reduction-in-CT-SEMAR.pdf

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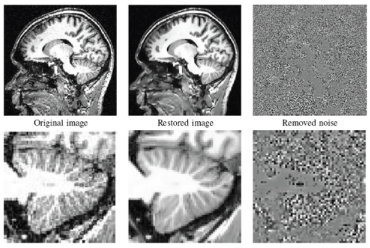
Image enhancement - Denoising



Hellier, TMI 2008

Denoising of brain MRI

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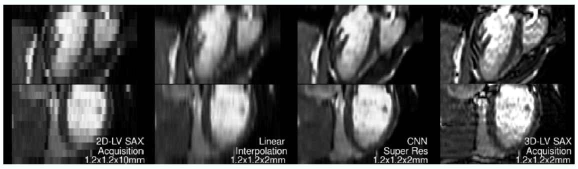
Image enhancement – Super-resolution

Low res acquisition

Baseline super-resolution method (linear interpolation)

Super-resolution using CNN

High resolution acquisition (ground truth)



O. Oktay et al. IEEE TMI 2017

Source: Daniel Rueckert, Imperial College London

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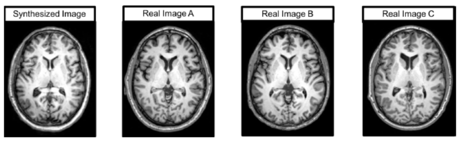
Image synthesis

Data augmentation



Source: Bermudez et al, Learning Implicit Brain MRI Manifolds with Deep Learning, SPIE MI, 2018

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Image translation

Synthesizing one modality from another

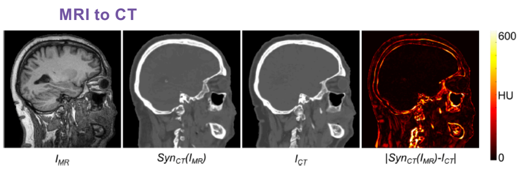

Fig. 4: *From left to right* Input MR image, synthesized CT image, reference real CT image, and absolute error between real and synthesized CT image.

Source: Wolterink et al, Deep MR to CT synthesis using unpaired data, 2017

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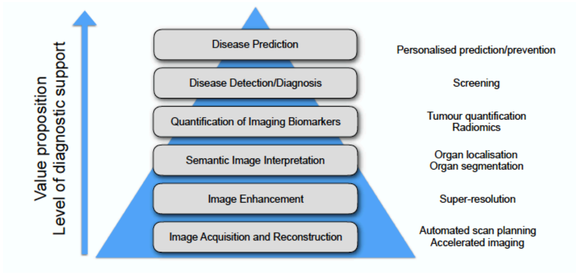
Tasks



Source: Daniel Rueckert, Imperial College London

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