Medical Image Analysis

Lessons

François Brunotte – Principles of filtered back projection and image reconstruction from projections - Analysis of kinetic images in nuclear medicine (example with cardiac scintigraphy)

Paul M. Walker – Magnetic Resonance Imaging and Spectroscopy; Imaging of Tumours

Alain Lalande - Concepts of Medical Image post-processing; MRI of the Heart

Alexandre Cochet – Nuclear Medicine

Christian Mata - Overview of deformable model. Overview of registration method. Little introduction about deep learning methods in medical imaging.

Assessment

Exam (35 %) (2 hours – books and course notes NOT allowed)

Project (35 %) (Deadline for the report: 22 may 2020)

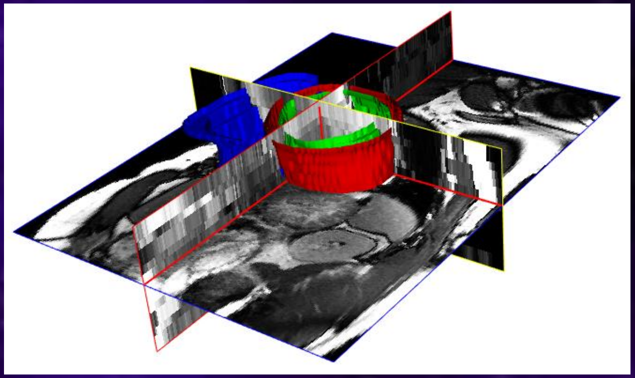
Defense of the project (20 %) with a demo of the developed software

(date: 26 may 2020 - 15 minutes + 10 minutes for questions)

Practicals (final report) (10 %)

Project (pair-work)
Project based on a challenge of the MICCAI conference

Automated Cardiac Diagnosis Challenge



Project (pair-work)
Project based on a challenge of the MICCAI conference

Automated Cardiac Diagnosis Challenge

ACDC

UNIVERSITÉ DE BOURGOGNE

CHU

Centre Hospitalier Universitaire Dijon

Creatis

MICCAI conference – Grand challenge

- MICCAI (Medical Image Computing and Computer Assisted Intervention) conference 2017 in Québec City

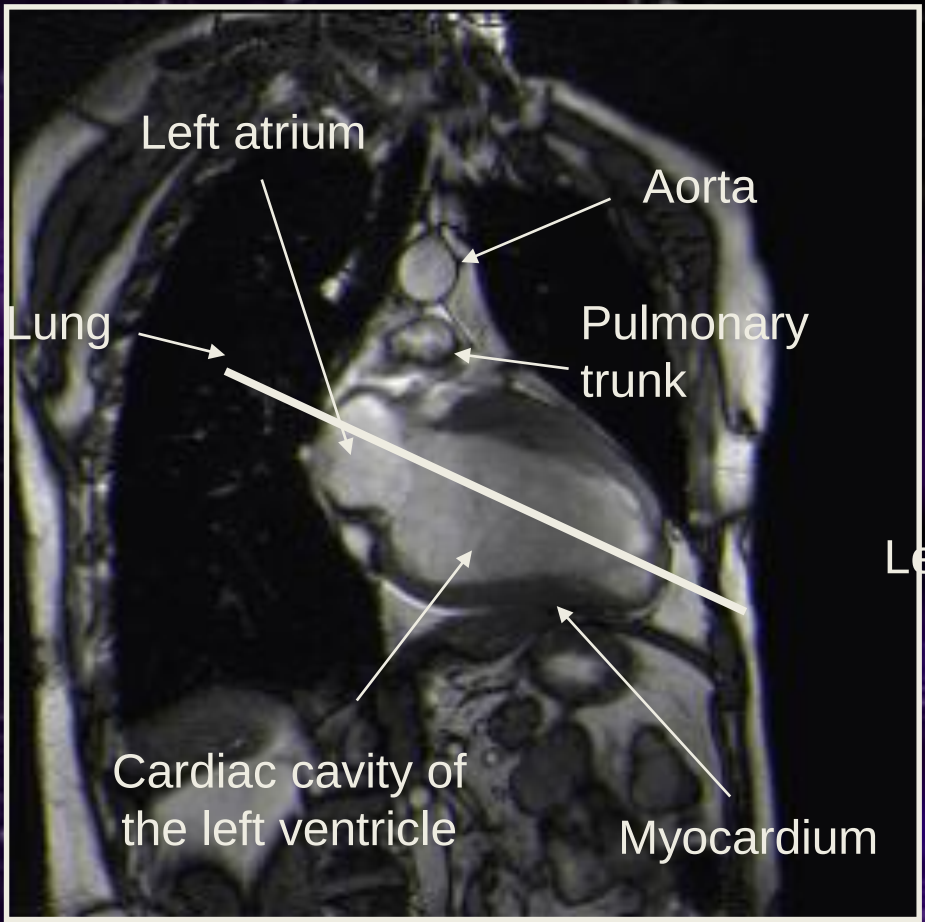
- During MICCAI, there are « Grand challenges in biomedical image analysis»

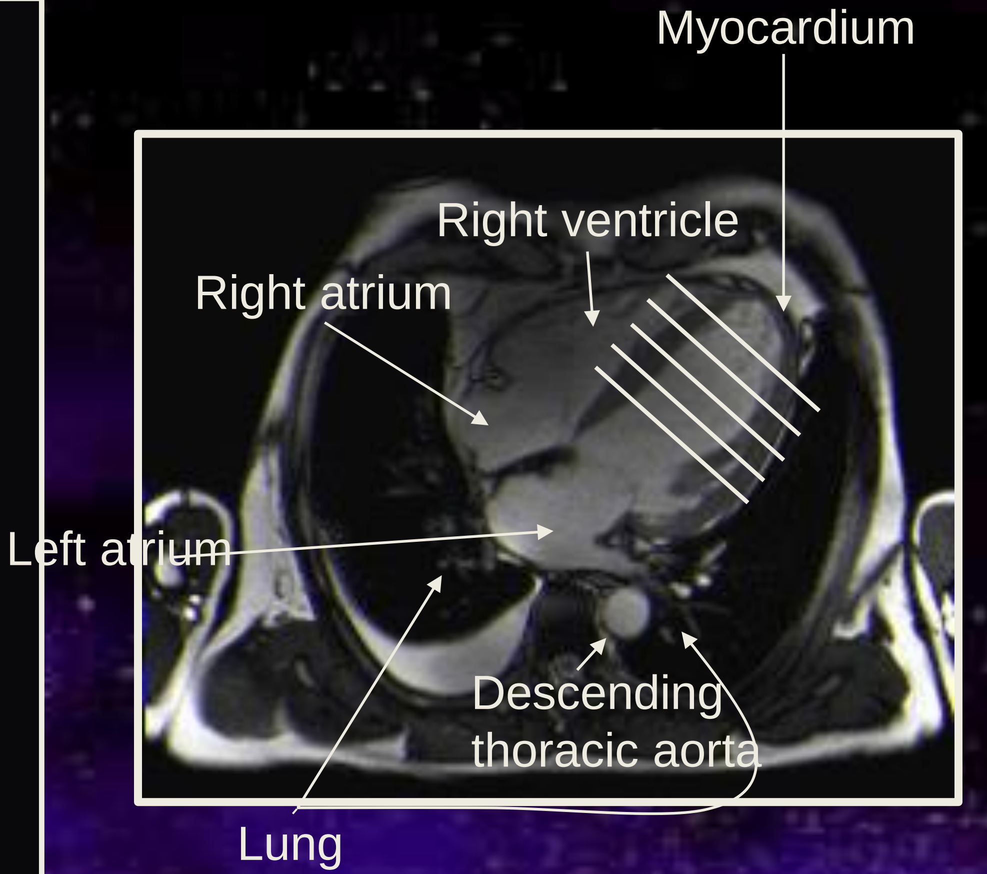
➔ Comparison of newly proposed and existing methods on the same data sets for a particular topic

➔ Highlight of the advantages and drawbacks of each method (ranking of the different methods)

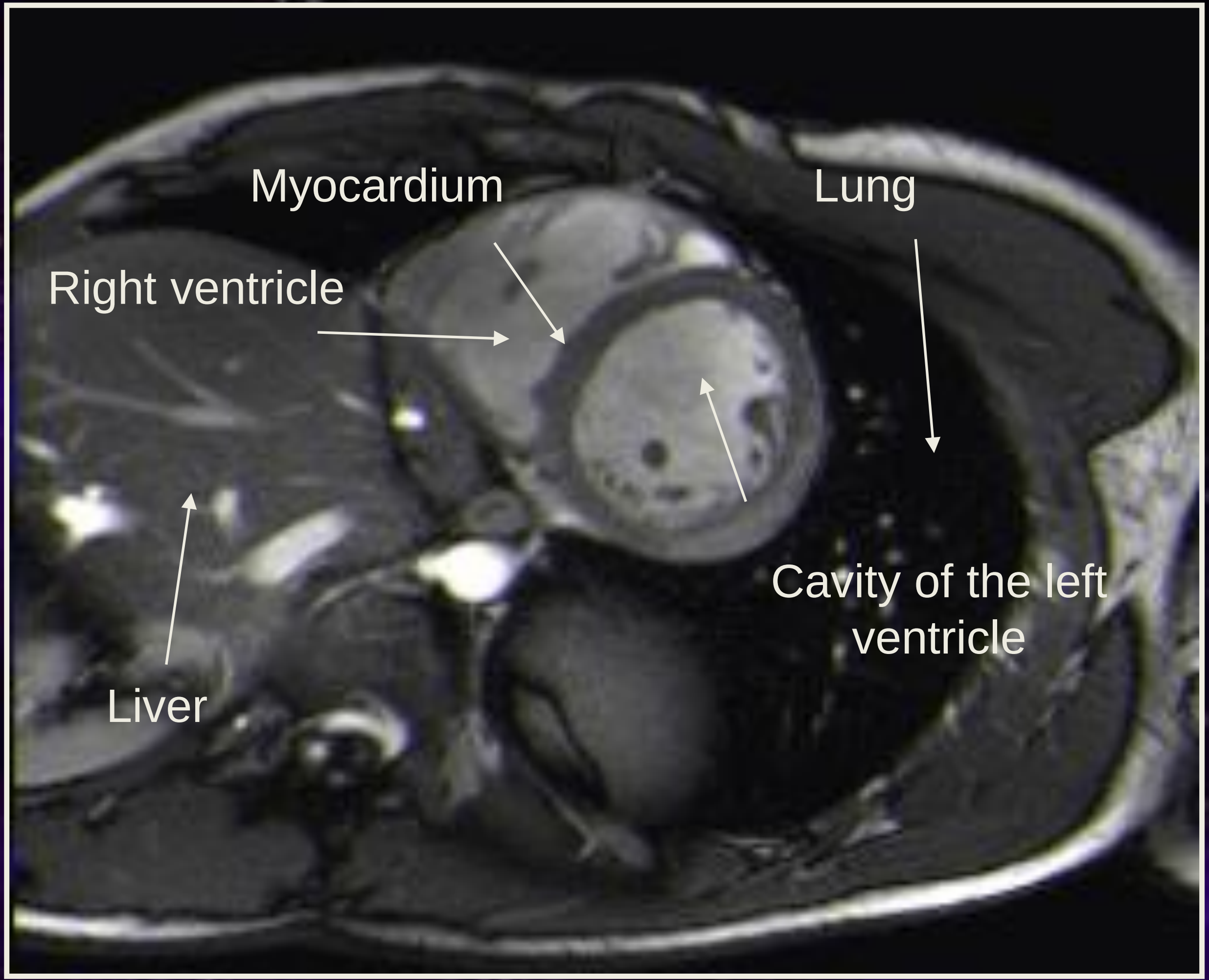
➔ Training data set available long time before the challenge and testing data set during a short period (and in our case still available)

Kinetic cardiovascular MRI





Kinetic cardiovascular MRI



Temporal resolution in clinical practice :
~ 20-30 msec / image

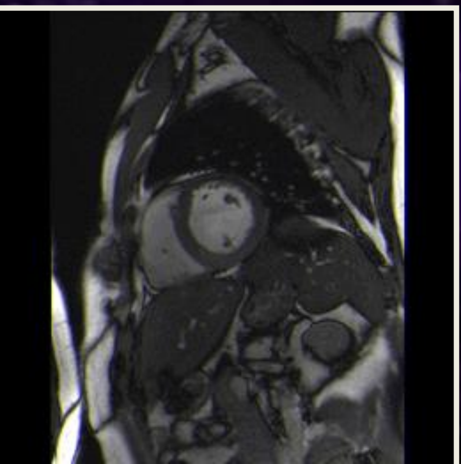
Left ventricular volume calculation

The left ventricular volume is calculated from the sum of the cardiac cavity area A_i measured on all short-axis slices covering the ventricle, multiplied by the sum of the slice thickness St and the slice gap Sg.

St: Slice thickness

Sg: Gap between two slices (if Sg = 0, image are contiguous)

$$V = (St+Sg) \sum_{i=1}^{n} A_i$$



The ejection fraction

The ejection fraction (EF) is the fraction of blood pumped out of a ventricle with each heart beat.

It is most used parameter to evaluate of the left ventricle contraction, and by extension the heart function.

Calculation with MRI:

$$EF = (DV - SV) / DV \times 100$$

DV : Diastolic volume (end-diastolic volume or <u>maximum volume</u>)
SV : Systolic volume (end-systolic volume or <u>minimum volume</u>)

Automated cardiac diagnosis challenge (ACDC) Challenge MICCAI / STACOM

➔ Statistical Atlases and Computational Modeling of the Heart (STACOM workshop) during the MICCAI conference.

<u>Framework</u>

- Post processing of cardiac cine-MRI in short axis orientations
- Database with different well-defined pathologies

<u>Objectives (two independant evaluations)</u>

1) Segmentation of the left ventricular endocardium and epicardium as the right ventricular endocardium on each diastolic and systolic images

2) Automatic classification of the examinations in five classes (normal case, systolic heart failure with infarction, dilated cardiomyopathy, hypertrophic cardiomyopathy, abnormal right ventricle)

Data base

150 MR examinations divided evenly into 5 classes :

- **Normal**

(EF > 50 %; wall thickness < 12 mm; diastolic LV volume < 90 mL/m² for men, < 80 mL/m² for women; normal right ventricle)

- **Systolic heart failure with infarction**

(EF <45%; several myocardial segments with abnormal contraction)

- **Dilated cardiomyopathy**

(diastolic LV volume >110 mL/m²; EF <40%; wall thickness in diastole < 12 mm; potentially abnormal high LV cardiac mass due to the pathology)

- **Hypertrophic cardiomyopathy**

(Several myocardial segments with a thickness higher than 15 mm in diastole with or without LV cardiac mass >110 g/m²; EF > 55%)

- **Abnormal right ventricle**

(Volume of the RV cavity>110 mL/m² for men or > 100 mL/m² for women, or EF of the RV<40%; more or less normal left ventricle)

Data

Conventional SSFP sequence and images in short axis slices

- 1,5 T or 3T Siemens whole body imager
- All the data acquired at the CHU of Dijon
- Slice thickness from 5 mm to 8 mm (in general, 5 mm)
- Distance between slices (slice gap) from 0 mm (contiguous slices) to 5 mm
- « Real life » examinations (variable quality, variable FOV, etc.)

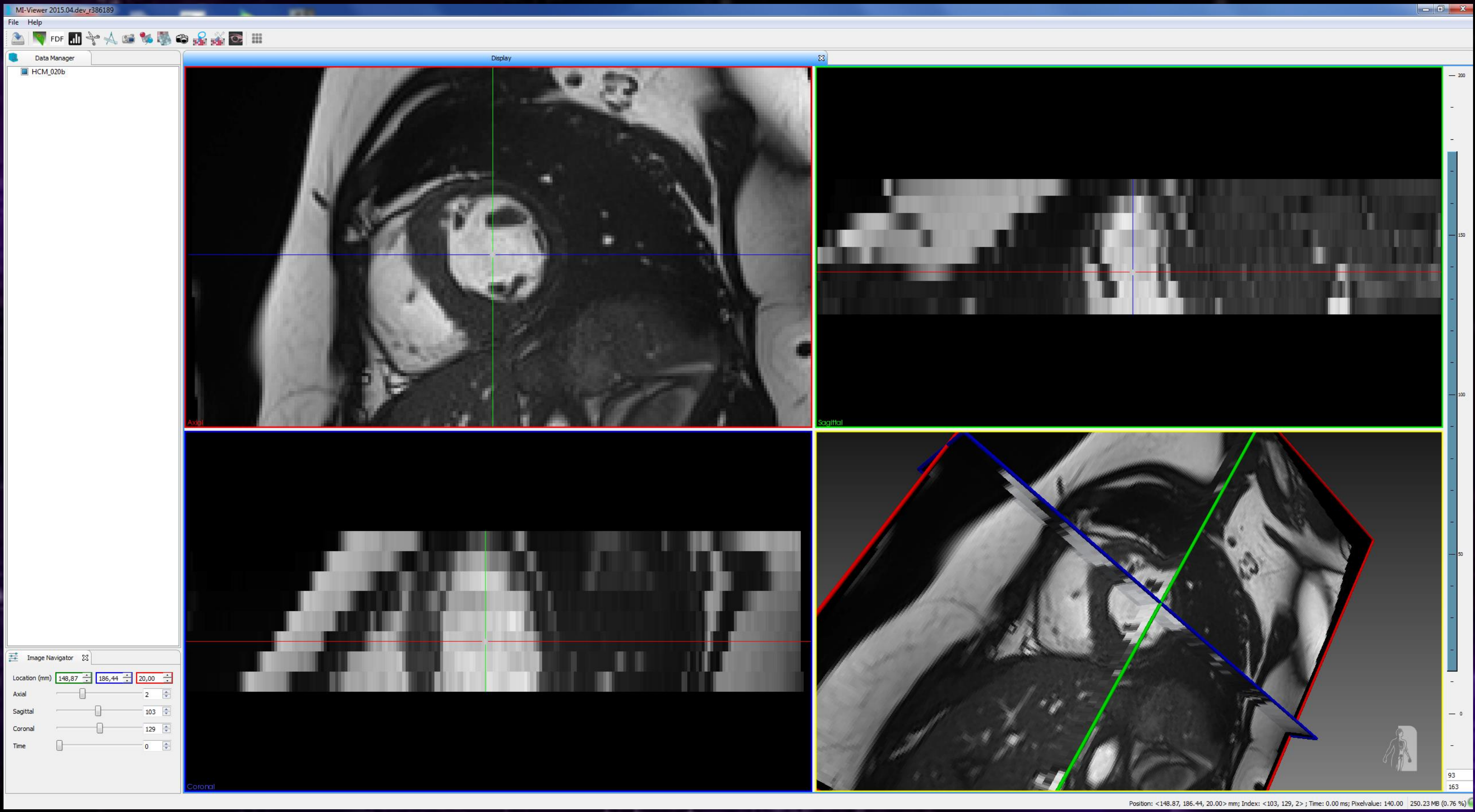
Conventional SSFP sequence and images in short axis slices

From DICOM data, examinations coded in Nifti format

Manual drawing from experts at the end-diastolic and end-systolic phases of :

- Endocardial border of the left ventricle
- Epicardial border of the left ventricle

Image format



Project (pair-work)

1/ Register on the website and download the database (only the training dataset)
➔ https://www.creatis.insa-lyon.fr/Challenge/acdc/

2/ Based on a scientific article (**to find**), develop a tool to segment the left ventricle in diastole and systole (only the endocardium)
Calculate the ventricular cavity volume in diastole and systole
➔ Tips about bibliographic research in the S1 lectures

3/ Report and software (**maximum 6 pages**) :
Little abstract presenting the topic, the context and the background.
Describe the used method and the developed tool
Discuss the results
➔ **deadline : 22 may 2020**

4/ Presentation and demonstration (**26 may 2020**)
15 minutes + 10 minutes for questions (try to do a demo)
Test of the software on your laptopt

Websites

https://www.creatis.insa-lyon.fr/Challenge/acdc/

http://stacom2017.cardiacatlas.org/

http://www.miccai2017.org

Articles

Bernard O,Lalande A, Zotti C, et al. Deep Learning Techniques for Automatic MRI Cardiac Multi-structures Segmentation and Diagnosis: Is the Problem Solved ? IEEE Transactions on Medical Imaging. 2018 Nov; 37(11): 2514-2525. doi: 10.1109/TMI.2018.2837502.

Petitjean C, Dacher JN. A review of segmentation methods in short axis cardiac MR images. Med Image Anal. 2011 Apr;15(2):169-84. doi: 10.1016/j.media.2010.12.004

Medical Image Analysis

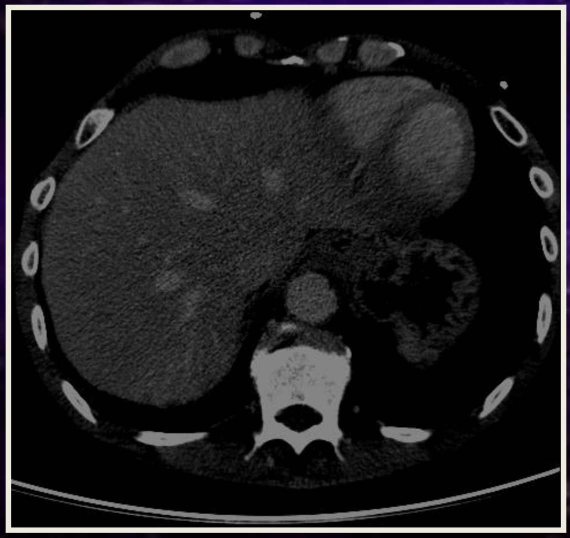
Concepts of medical image post-processing

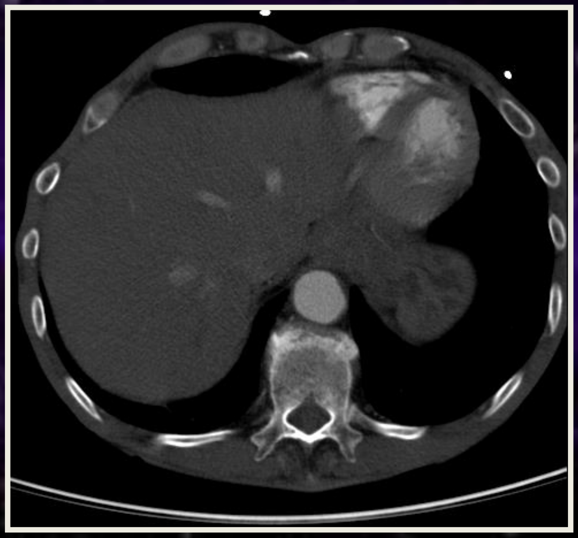
Alain LALANDE
alain.lalande@u-bourgogne.fr

Why is *Medical* Image Analysis Special ?

- Because of the *patient*
  - Each patient (or case) is different

- Because of *Radiology*
  - Medical decisions made on sufficient information
  - Part of the care cycle (aid in the diagnosis, aid in the therapy)
  - Not in "theory land"
  - Some advantages of dealing with medical images ➔ A priori information (knowledge of what is and what is not normal human anatomy. Selective enhancement of specific organs or objects via injection of contrast-enhancing material).



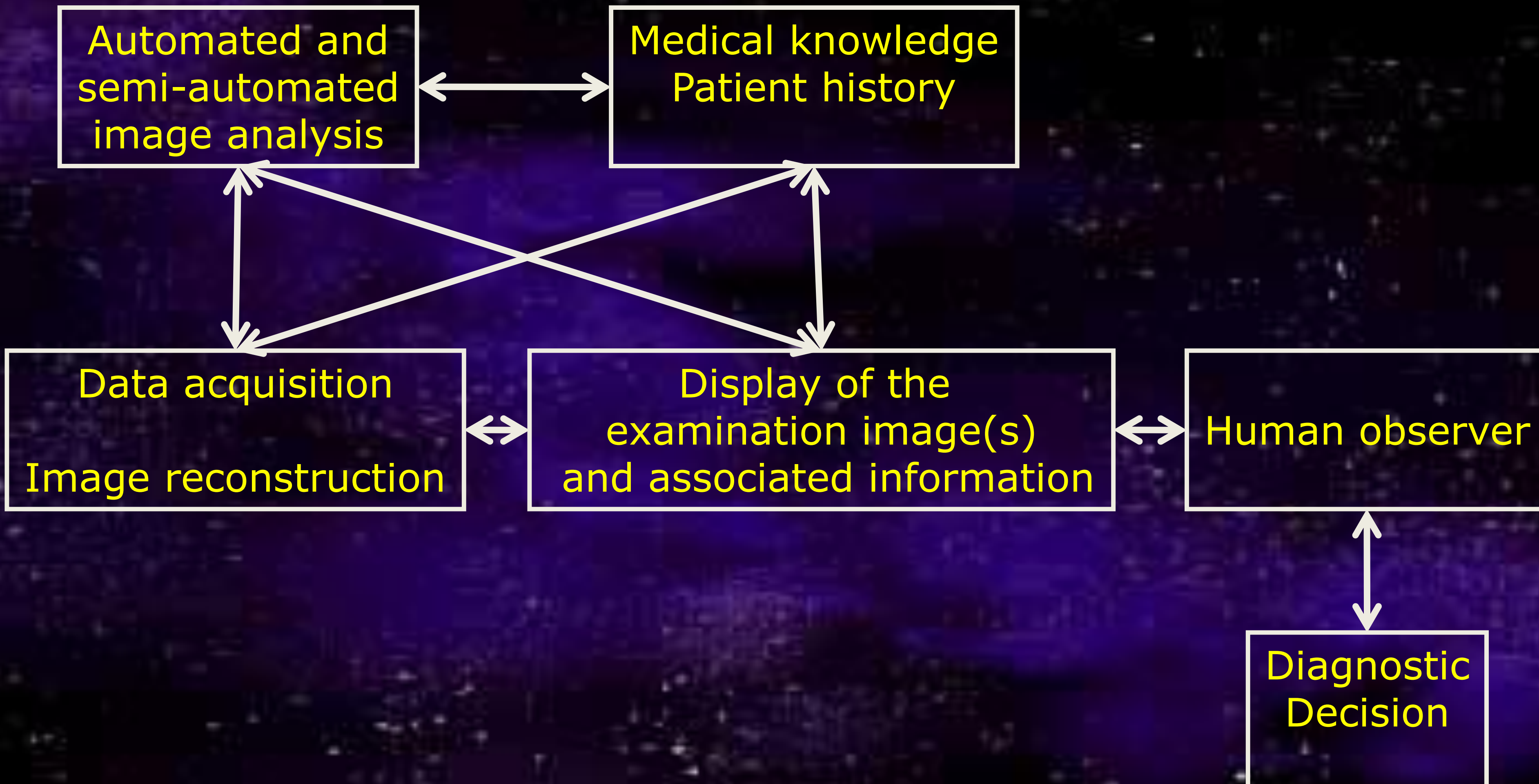


Why is *Medical* Image Analysis Special ?

- From physic to information processing

  - Understanding physic of imaging.
  - Understanding imaging instrumentation (signal to noise ratio, collection of the data, resolution, etc.).
  - Image reconstruction (pre-processing, back-projection, enhancement, etc.)
  - Development of techniques to supplement the mostly qualitative and frequently subjective assessment of medical images by human experts.
  - Providing a variety of new information that is quantitative, objective and reproducible.

- Ultimate goal : Complete image understanding within a computer to perform diagnosis and control robotic intervention


Automated and semi-automated image analysis
Medical knowledge
Patient history
Data acquisition
Image reconstruction
Display of the examination image(s) and associated information
Human observer
Diagnostic Decision

What is medical image post-processing ?

Data acquisition

Image reconstruction

Automated and semi-automated image analysis

Preprocessing

Display

Reporting

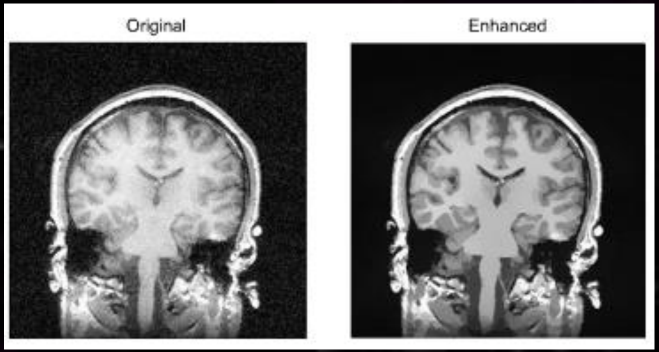
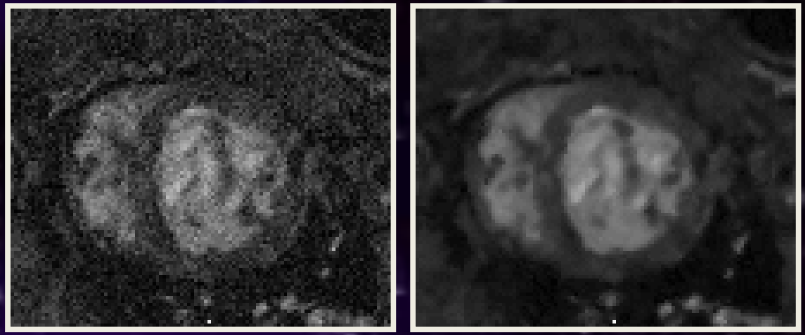


Image enhancement



Noise reduction

Improvement of image quality

What is medical image post-processing ?

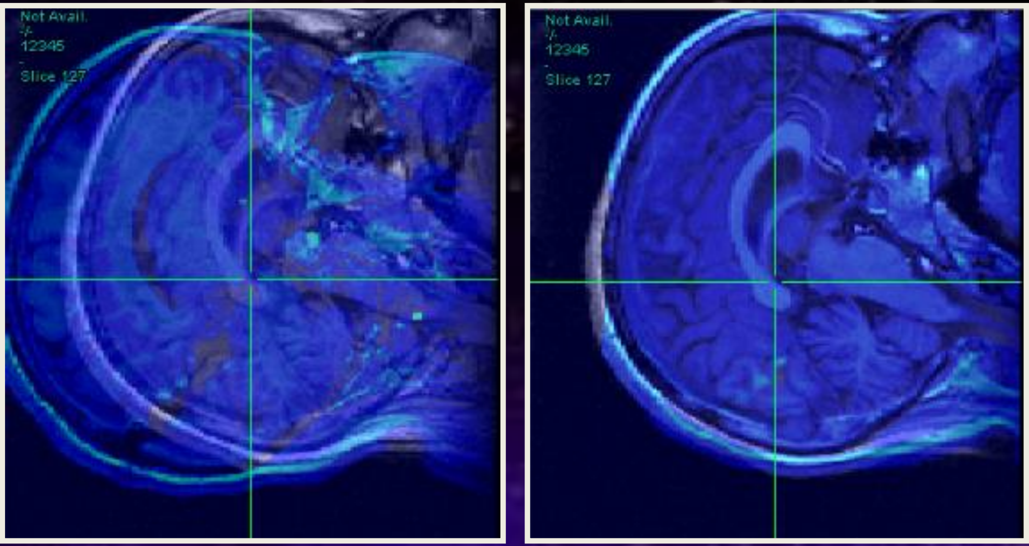
Data acquisition

Image reconstruction

Automated and semi-automated image analysis

Preprocessing

Registration



Alignment of data from one or several images

Display

Reporting

What is medical image post-processing ?

Data acquisition

Image reconstruction

Automated and semi-automated image analysis

Display

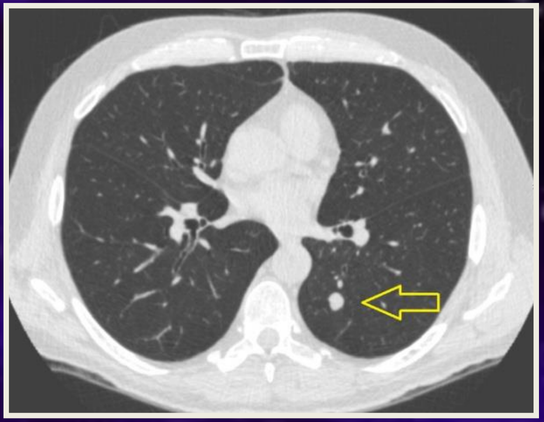
Reporting

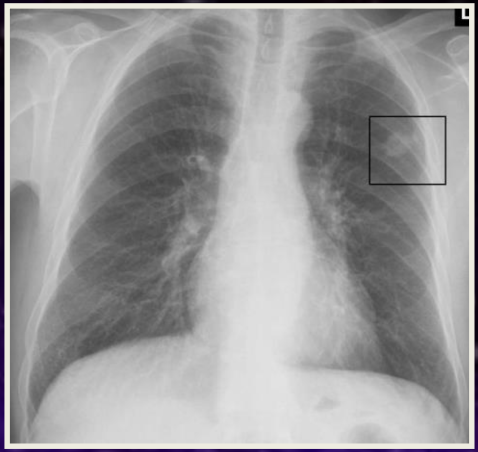
Preprocessing

Registration

Detection

Bones
Organs
Polypes
Tumors
…..





Nodules in the lung

Find the location of objects (structures)

What is medical image post-processing ?

Data acquisition

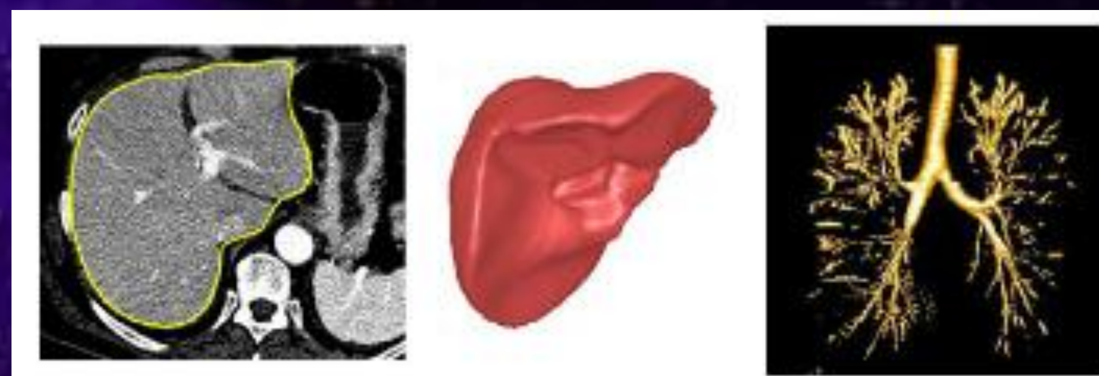
Image reconstruction

Automated and semi-automated image analysis

- Preprocessing
- Registration
- Detection
- Segmentation

Display

Reporting



<u>Find the boundaries of objects (structures)</u>

What is medical image post-processing ?

Data acquisition

Image reconstruction

Automated and semi-automated image analysis

Display

Reporting

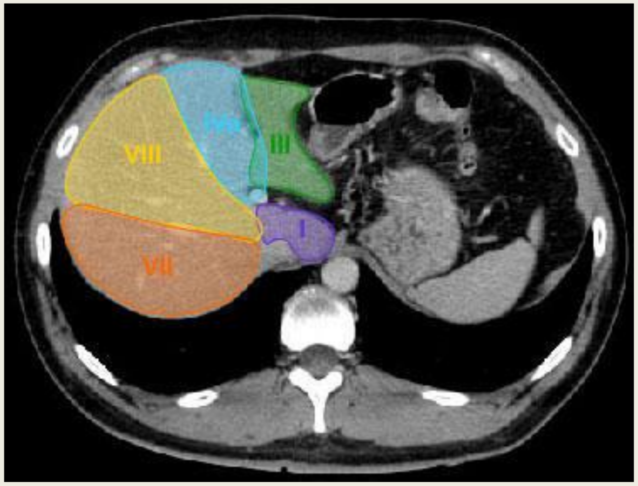
Preprocessing

Registration

Detection

Segmentation

Classification



Liver segment classification from CT

<u>Determine the type of objects (structures)</u>

What is medical image post-processing ?

Data acquisition

Image reconstruction

Automated and semi-automated image analysis

Display

Reporting

Preprocessing

Registration

Detection

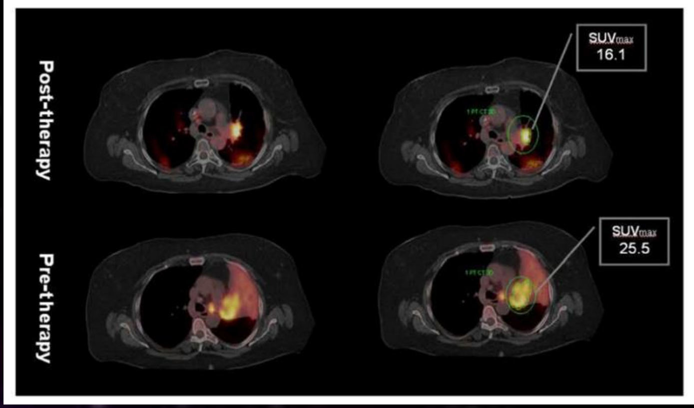
Segmentation

Classification

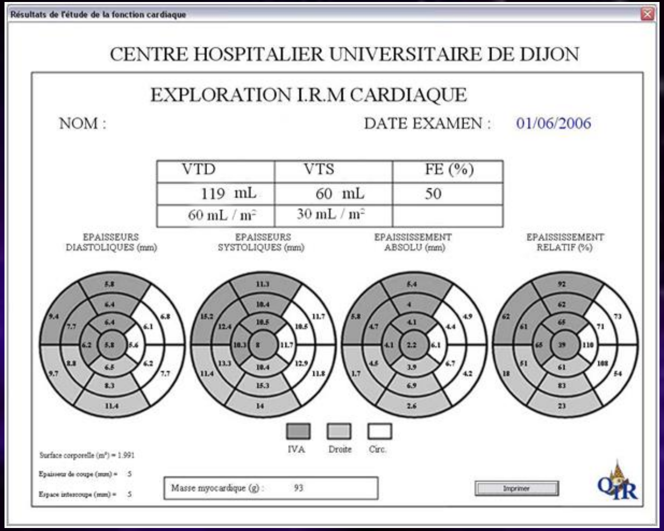
Quantification

<u>Parameter extraction</u>

<u>Comparison of normal and pathology anatomy</u>



Tumor volume and metabolims (SUV_{max})



Report from cardiovascular MR examination

What is medical image post-processing ?

Data acquisition

Image reconstruction

Automated and semi-automated image analysis

Display

Reporting

Preprocessing

Registration

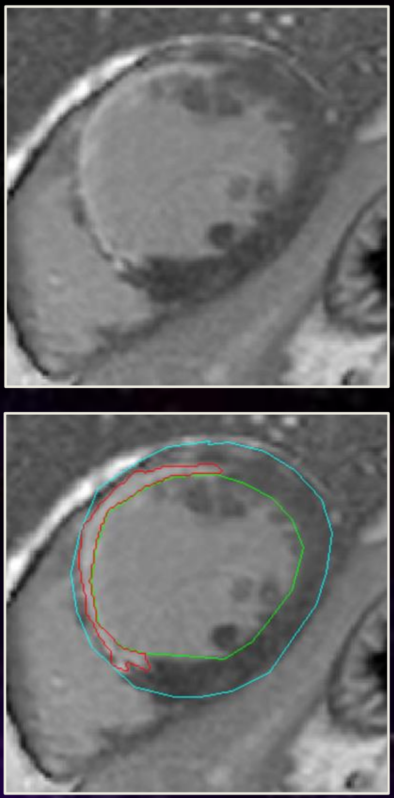
Detection

Segmentation

Classification

Quantification

Diagnosis



Myocardial infarction in the septum
(12 % of the whole myocardium)

Classification as normal vs abnormal, or benign vs malignant,or cancer vs non cancer, etc.

What is medical image post-processing ?

Data acquisition

Image reconstruction

Automated and semi-automated image analysis

Display

Reporting

Preprocessing

Registration

Detection

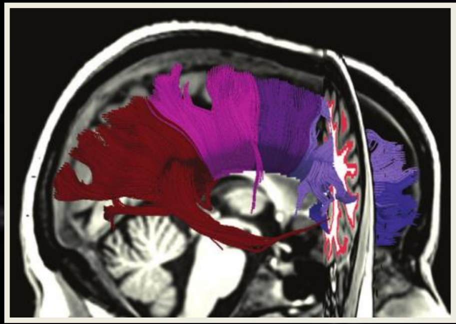
Segmentation

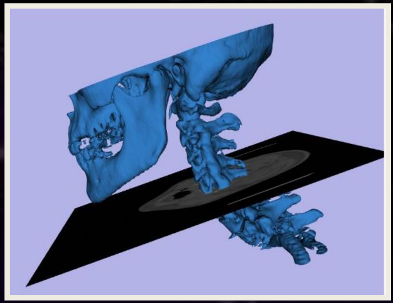
Classification

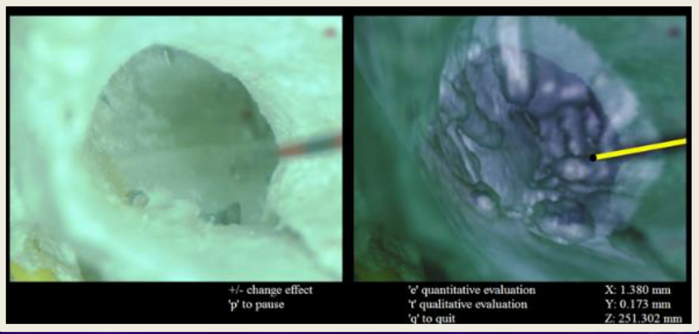
Quantification

Diagnosis

Visualization







<u>Representation of the images (only the desired objects can be see)</u>

<u>Augmented reality</u>

Types of image

- Binary image, gray level image, color image, false color image…

- Infrared, ultraviolet, X-ray (and tomodensitometry (CT)), MRI, ultrasound, optical, microwave …

- Dimension: 2D, 2D + Time, 3D, 4D (3D + Time)

- Radiographic film or digital image

- Format : raw data, Analyse, DICOM, standard formats (Tiff, JPEG, GIF, PNG, BMP, etc.).

➔However, DICOM is the standard format for handling, printing and transmitting information in medical imaging.
(cf lecture on Medical Imaging Sensors)

Image vs Object

- Images (and vision) are two-dimensional
  - Surface images
  - Projection images
  - Sectional images (tomographic technics)

- Image eliminates data
  - 3D object vs 2D image
  - Moving object vs still image

➔ Corruption during image formation

Ideal $f(x,y)$ → Camera, CT, MRI, … → Measured $g(x,y)$

No measuring device is perfect (insertion of noise, artefacts, etc.)

$g(x,y) = \mathrm{D}(\ f(x,y)\ )$, where D is the distortion function

Segmentation

- Labeling every voxel
- Identify anatomical areas of interest
- There are many methods !
- How good is the segmentation (how right are such label) ?
    - ➔Tremendous oversimplification
    - ➔ In general require a model

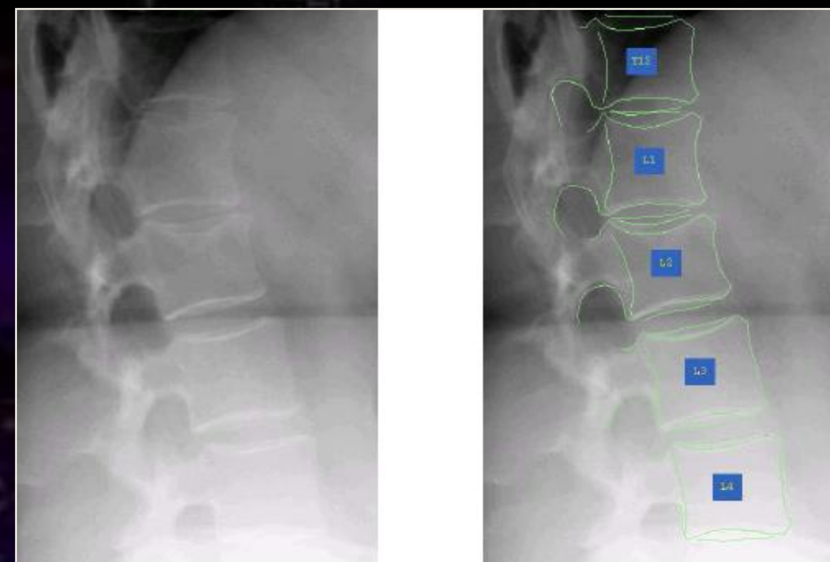
Discrete vs Fuzzy method

- Rigid method of segmentation that identifies every pixel as belonging to one and only one class
- Fuzzy method of classification may define fractional mixing between classes

Medical image segmentation

2D segmentation

Detected contours of phalanges on a X-ray radiography



Segmentation of lumbar vertebrae on a X-ray radiography

de Luis-Garcia et al, ICIP 03; 618-638; 2003

Roberts et al, Academic radiology, 14(10); 1156-1165; 2007

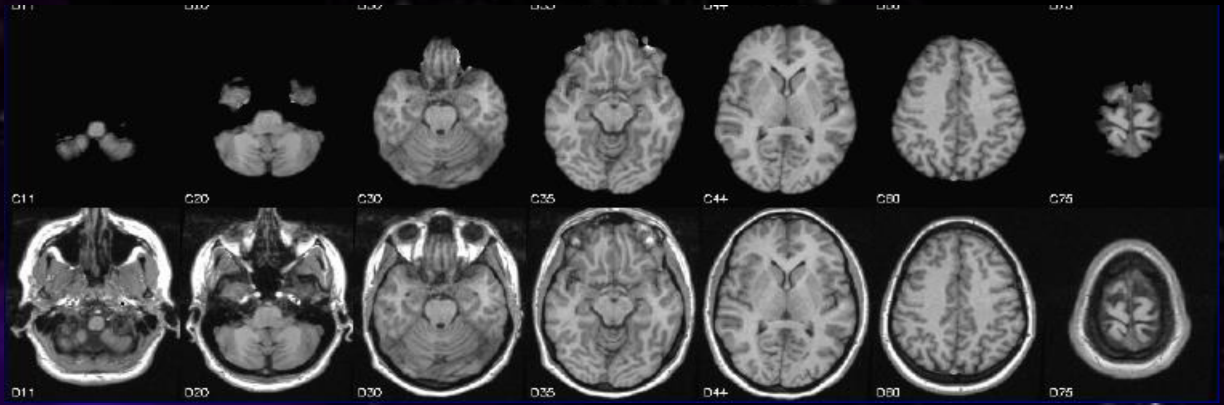
Medical image segmentation

Pseudo 3D segmentation

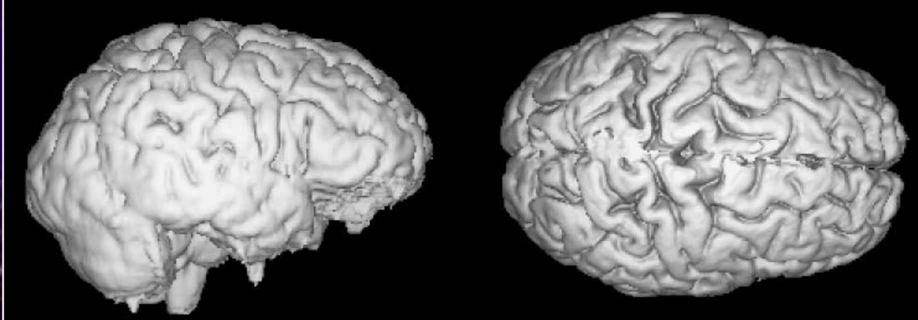
Segmentation of the brain surface from MRI.

Segmented images

Initial images



The segmentation consists in a threshold followed by the application of a mask (a coarse brain mask is used to limit the segmentation to the brain) and a smoothing filter.



3D reconstruction

Medical image segmentation

3D reconstruction and segmentation

PET (breast cancer)

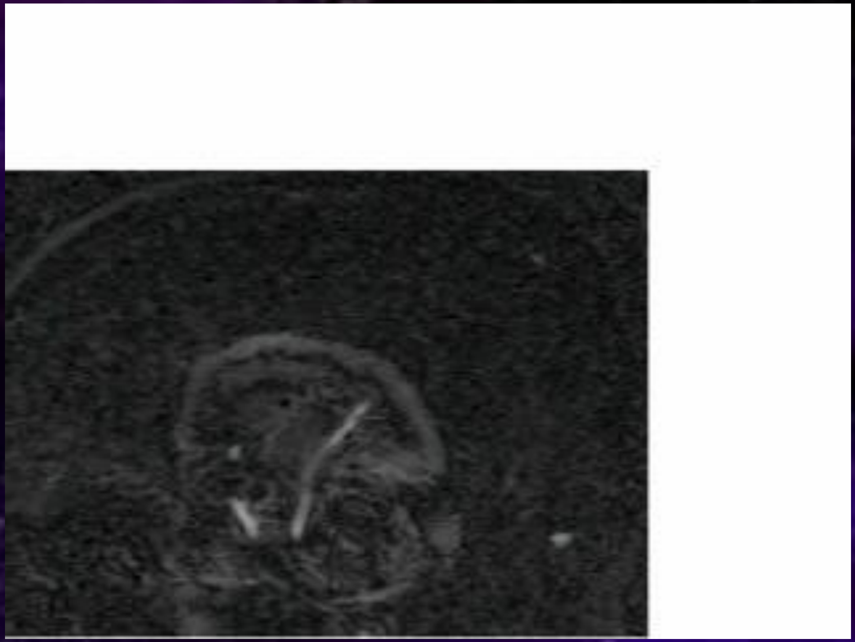
Real-time 3D image reconstruction
from CT data

Soler et al, Hepatobiliary Surg Nutr; 3(2): 73–81; 2014

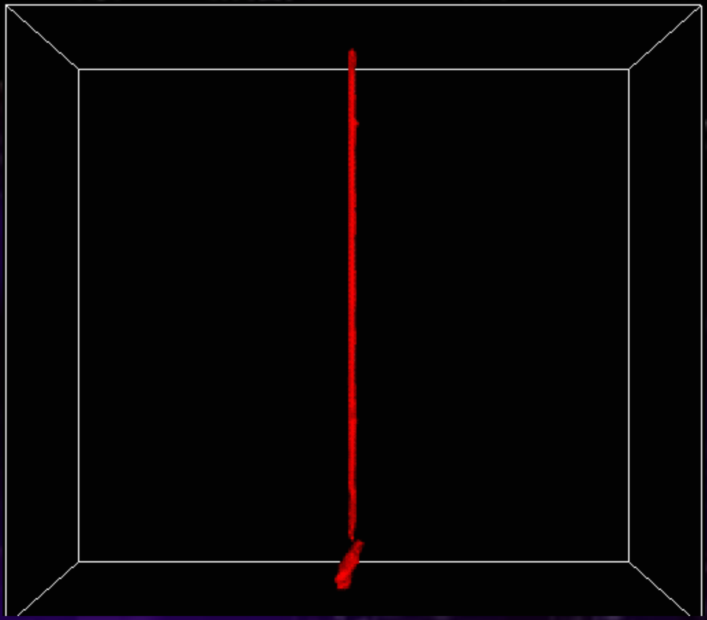
Medical image segmentation

3D segmentation

Vessel segmentation from MR angiographic images



Raw data from MR angiography
Images are obtained after
contrast-agent injection

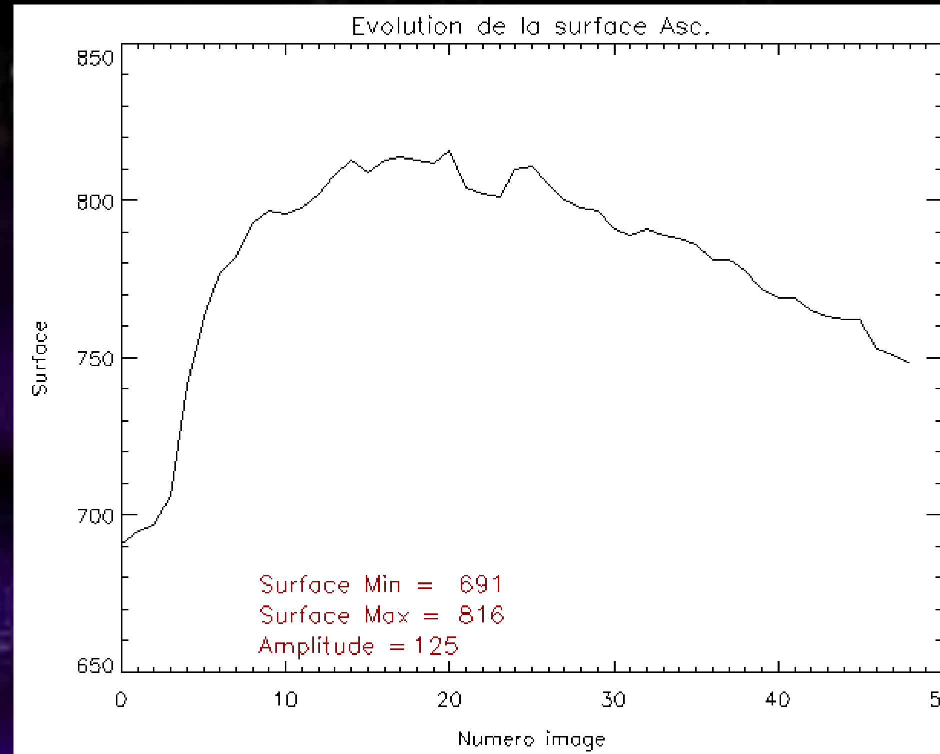


3D reconstruction after image segmentation (segmentation from geodesic active contours)

Lorigo et al, IPMI 1999.

Medical image segmentation

2D + Time segmentation



Automatic detection of the thoracic aorta contour on several images covering the cardiac cycle on one slice.

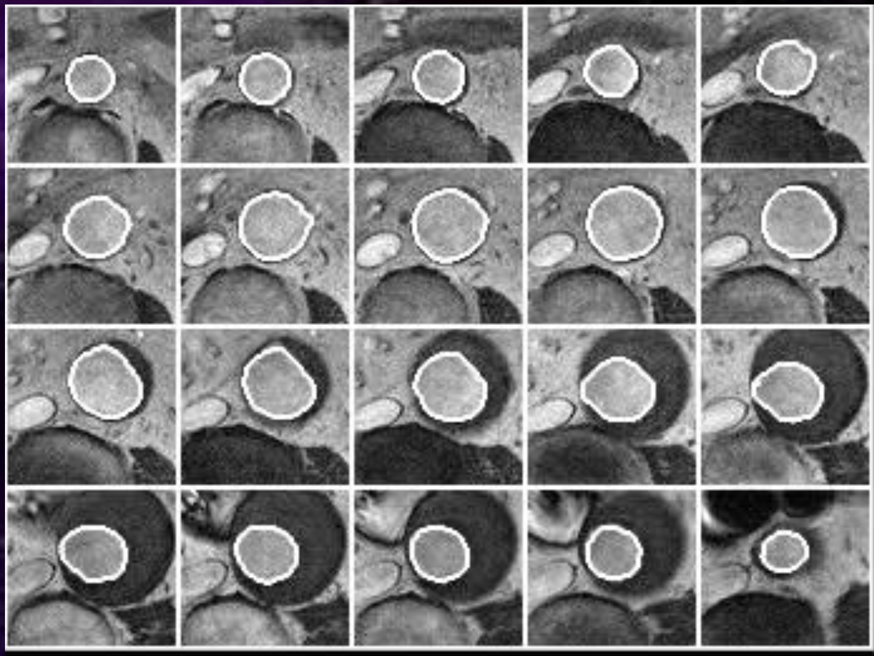
$$\text{Compliance}(mm^2/mmHg) = \frac{\Delta S}{\Delta P}$$

C = 3,47 mm² / mmHg

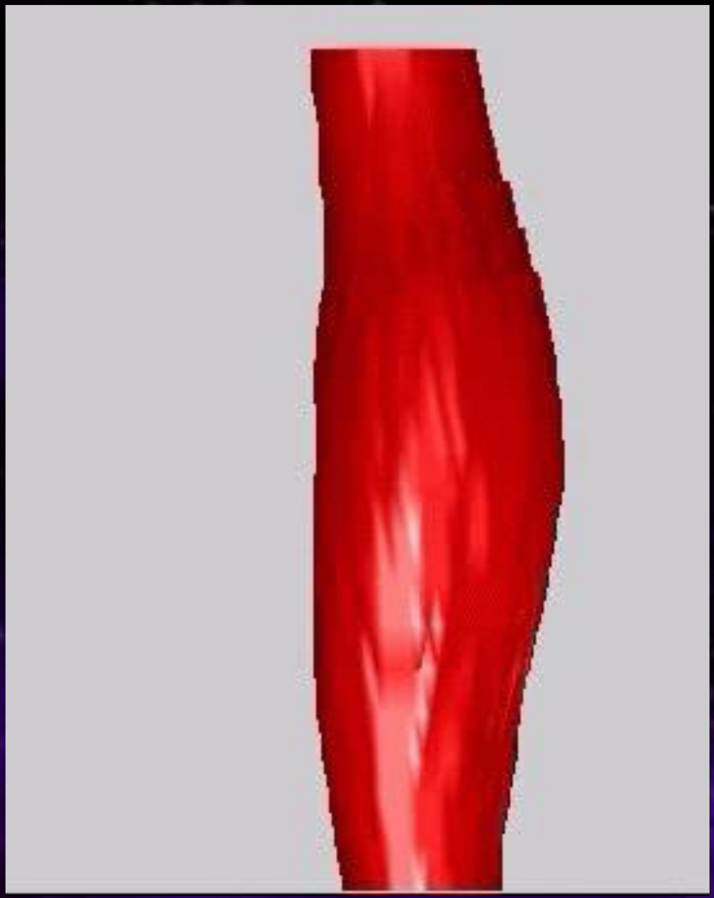
Lalande et al, Invest Radiol. 37(12); 685-91; 2002
Rose et al, MRI, 28; 255-263; 2010.
Zhu et al, Nature Genetics, 33; 343-349; 2006.

Medical image segmentation

Pseudo 4D segmentation (3D + Time)



Segmentation of the lumen of the abdominal aorta on several contiguous slices (use of a Markovian method)



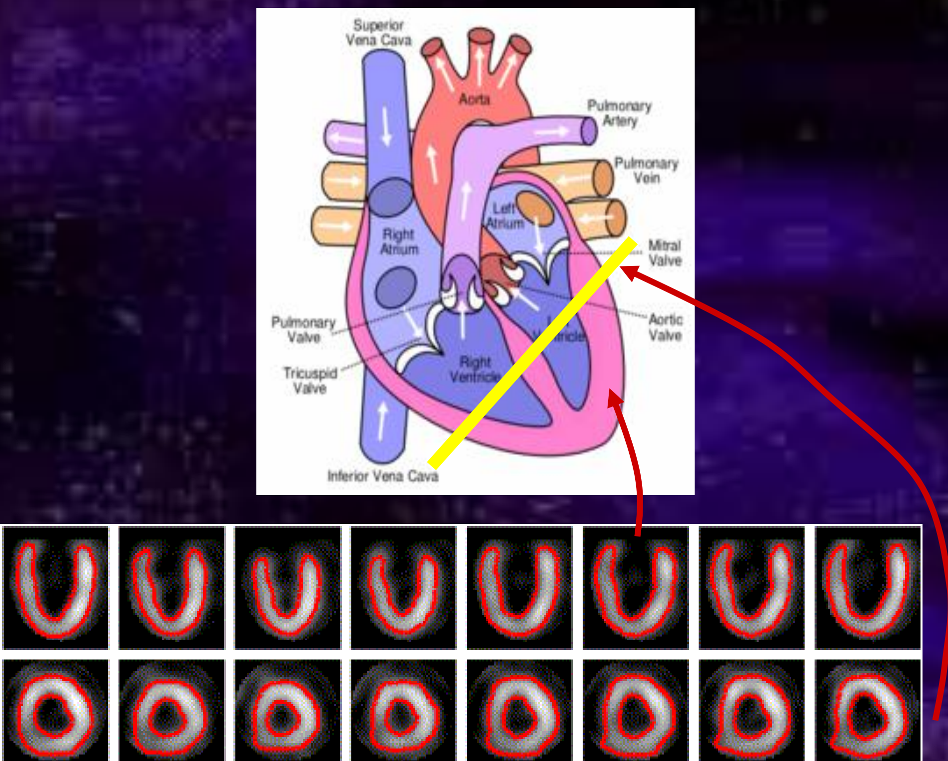
3D reconstruction

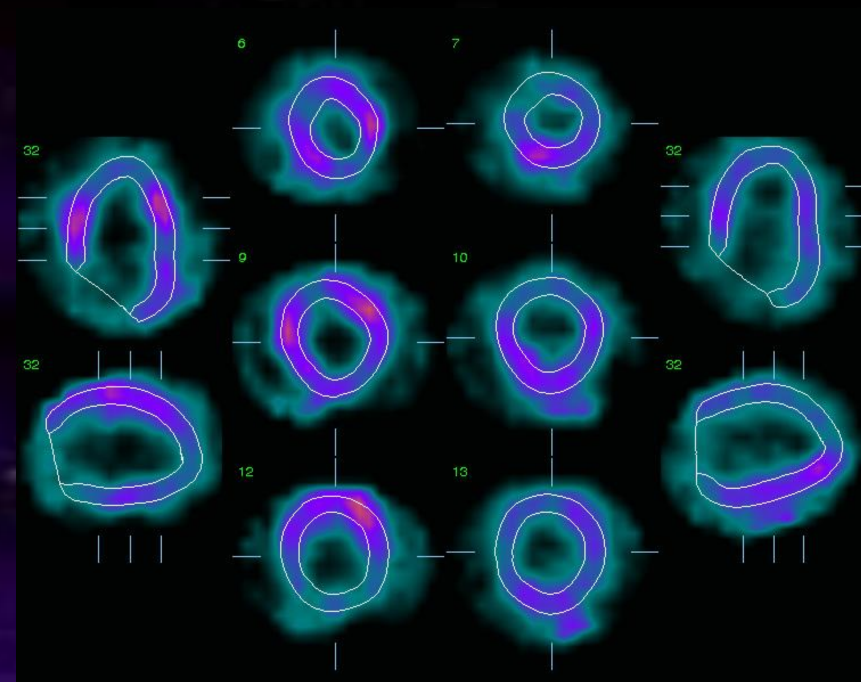
Jodoin et al, ICIP 08; 3012-3015; 2008

Medical image segmentation

4D segmentation (3D + Time)

In nuclear medicine, a cardiac SPECT scan provides true 3D information.





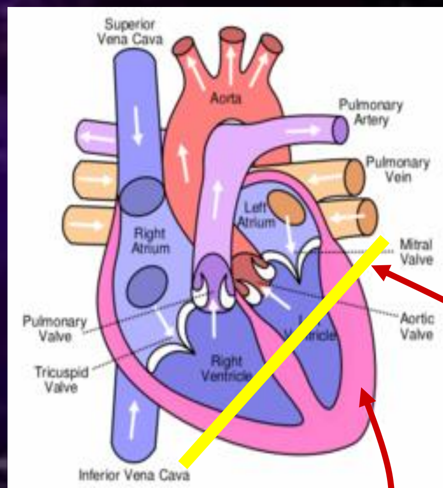
Tracking of the left ventricle in a 4D SPECT sequence

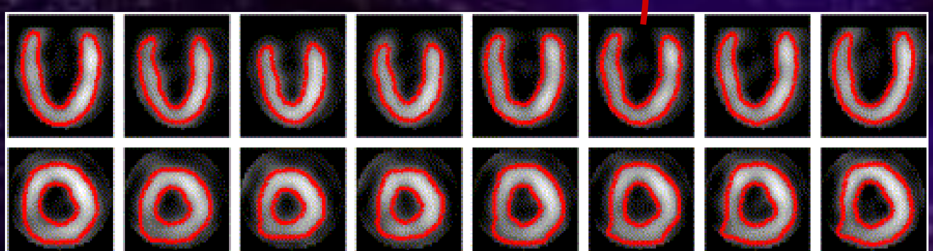
Sermesant et al, Medical Image Analysis 7(4); 475-488; 2003

Medical image segmentation

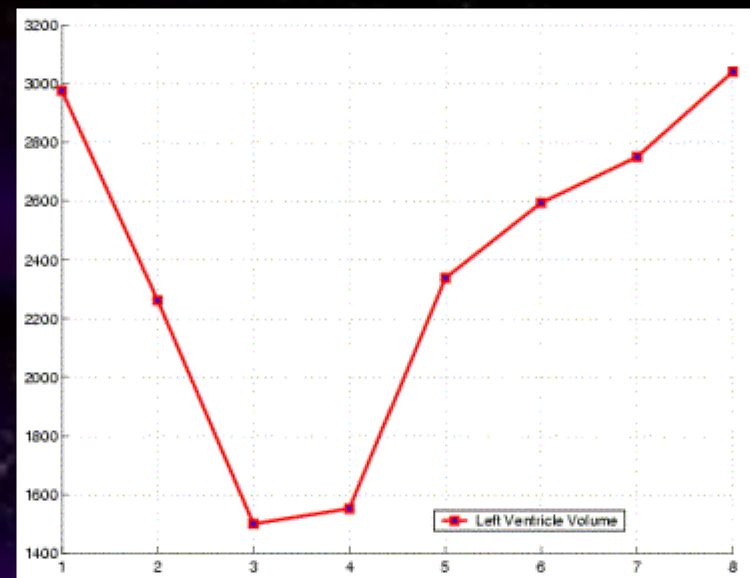
4D segmentation (3D + Time)

In nuclear medicine, a cardiac SPECT scan provides true 3D information.





Tracking of the left ventricle in a 4D SPECT sequence



Left ventricle volume evolution during the 8 SPECT image time sequence

Sermesant et al, Medical Image Analysis 7(4); 475-488; 2003

Medical image segmentation
What about deep learning approaches ?

Advantages

➔ Completly automatic methods
➔ Outperform the other state-of-the-art methods
➔ Provide excellent results in more than 95% of the images

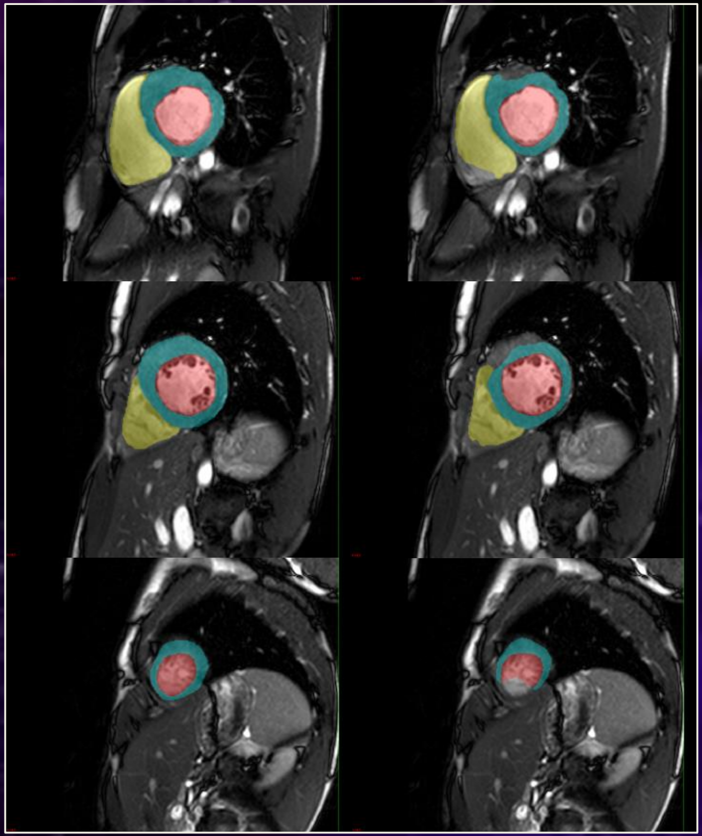
Drawbacks

➔ Can provide totally aberrant results because no a priori informations are taken into account (in particular about the anatomy)
➔ Require huge dataset with expertise for the training phase (and this is not evident in medical image domain)
➔ Require dataset from differents clinical centers, otherwise the method is not robust at all to different dataset
➔ Require powerful computers for the training phase (and sometimes for routine use)

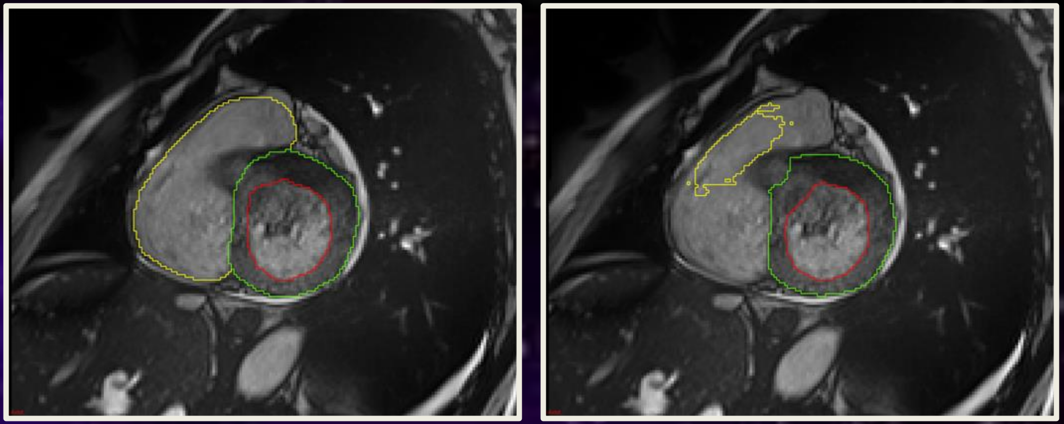
Futures

➔ Deep learning is a tool, not an aim
➔ Clinical objectives must be clearly and fully controlled, to avoid silly results (a good Dice index can hide an incorrect method)
➔ Use of a priori information

Medical image segmentation
What about deep learning approaches ?



GT



GT

During the ACDC challenge, for the best method, 41 patients out of 50 had at least one slice with an anatomically impossible segmentation

Bernard O,Lalande A, Zotti C, et al. IEEE Transactions on Medical Imaging. 2018 Nov; 37(11): 2514-2525.