STIC AmSud Project

Graph cut based segmentation of cardiac ventricles in MRI: a shape-prior based approach

Caroline Petitjean

A joint work with Damien Grosgeorge , Pr Su Ruan, Pr JN Dacher, MD

October 22, 2014

First of all…

- A little presentation ☺
- Electronics and Signal processing engineer (1999)
- PhD thesis (2003) from GET/INT (Paris):

Non rigid registration using statistical variational approaches.

Application to the analysis and the modelling of the myocardial function in MRI

First of all…

- Assistant Professor (since 2005) at the University of Rouen (**LITIS Lab**)
  - Image analysis and pattern recognition

    Mostly for:

    medical image segmentation (model-based, PDE-based…)

    medical image classification

    But also:

    image retrieval

Close collaboration with medical doctors (nuclear medicine doctors, radiologists…)

Close collaboration with Laurent (the one here in this room) and other colleagues

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Graph cut based segmentation of cardiac ventricles in MRI: a shape-prior based approach

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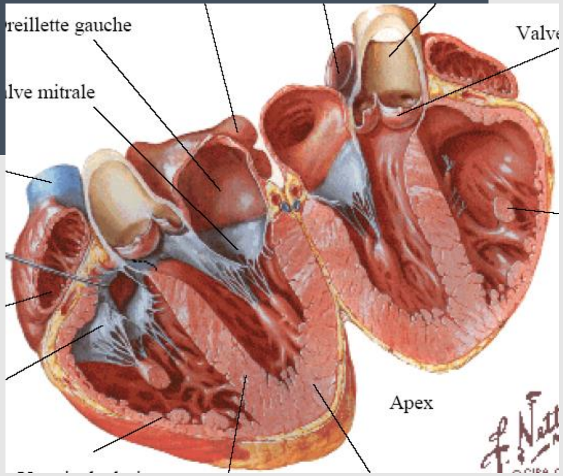
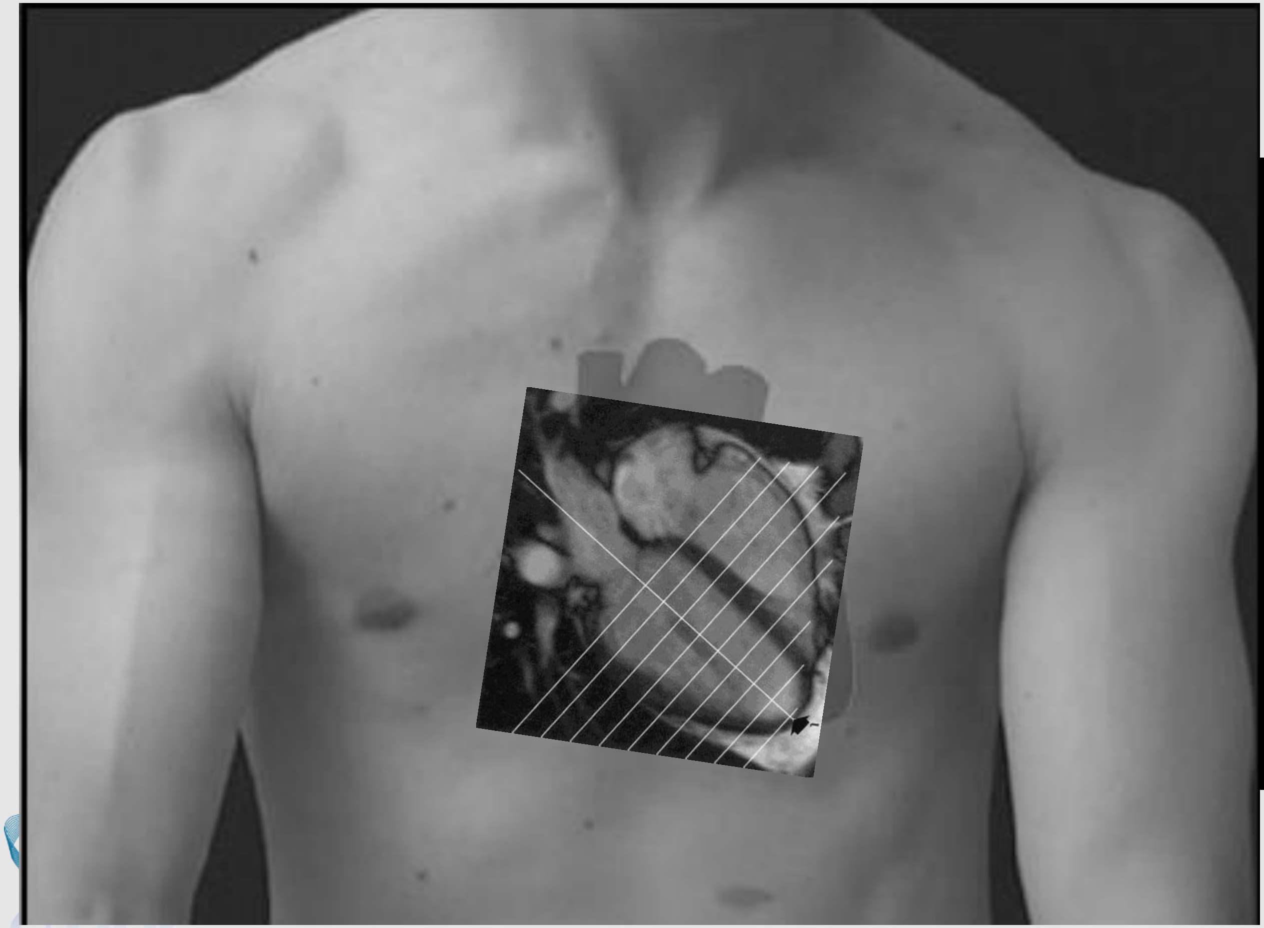
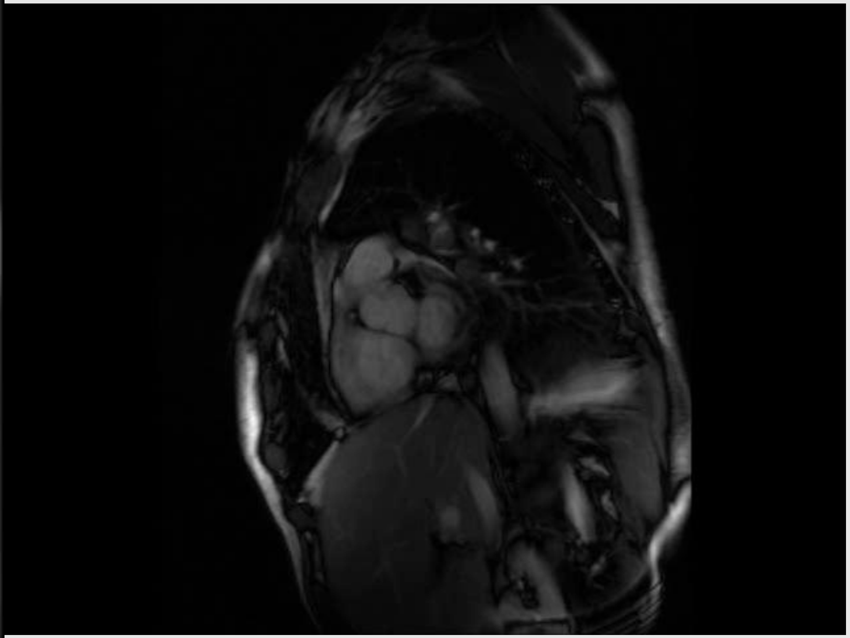
Context



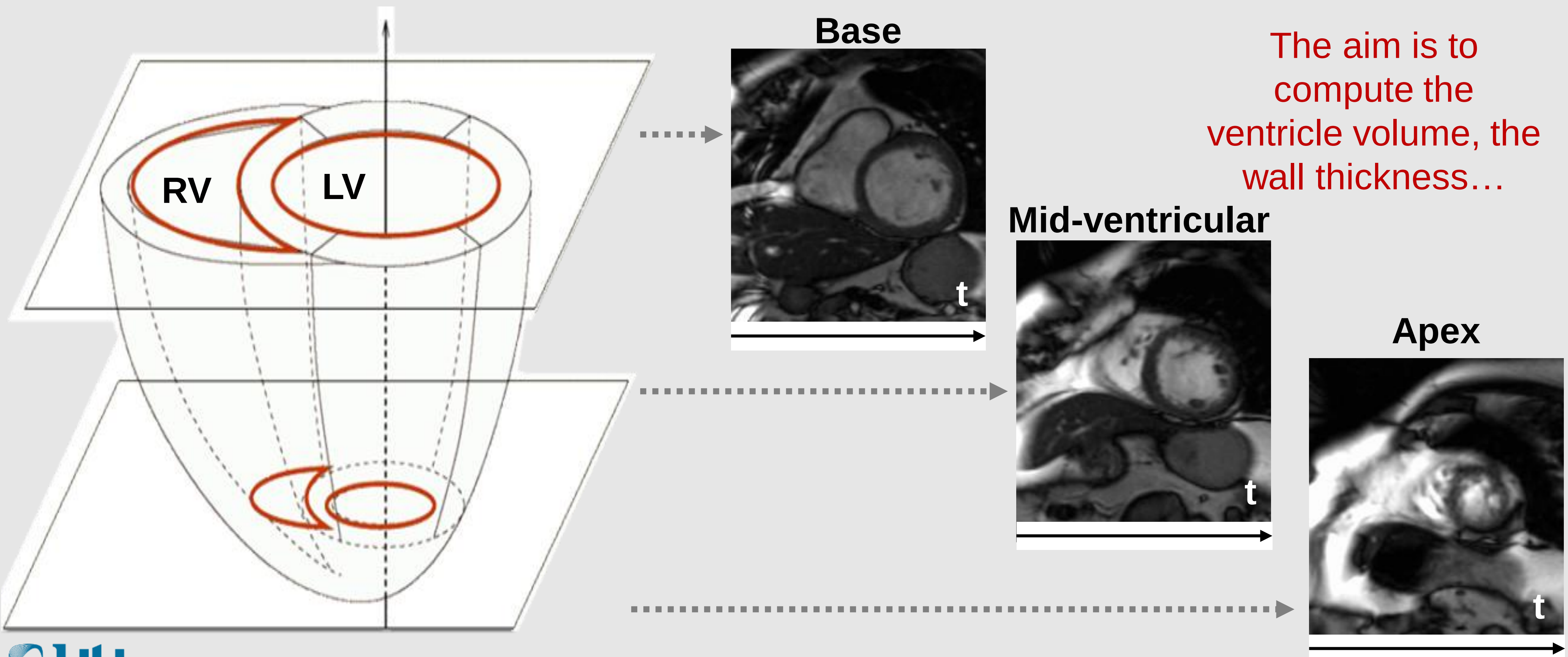
- Cardiovascular diseases:
  - A major cause of death in many countries
  - **Magnetic Resonance Imaging (MRI)** is a good tool to assess the cardiac contractile function





Context

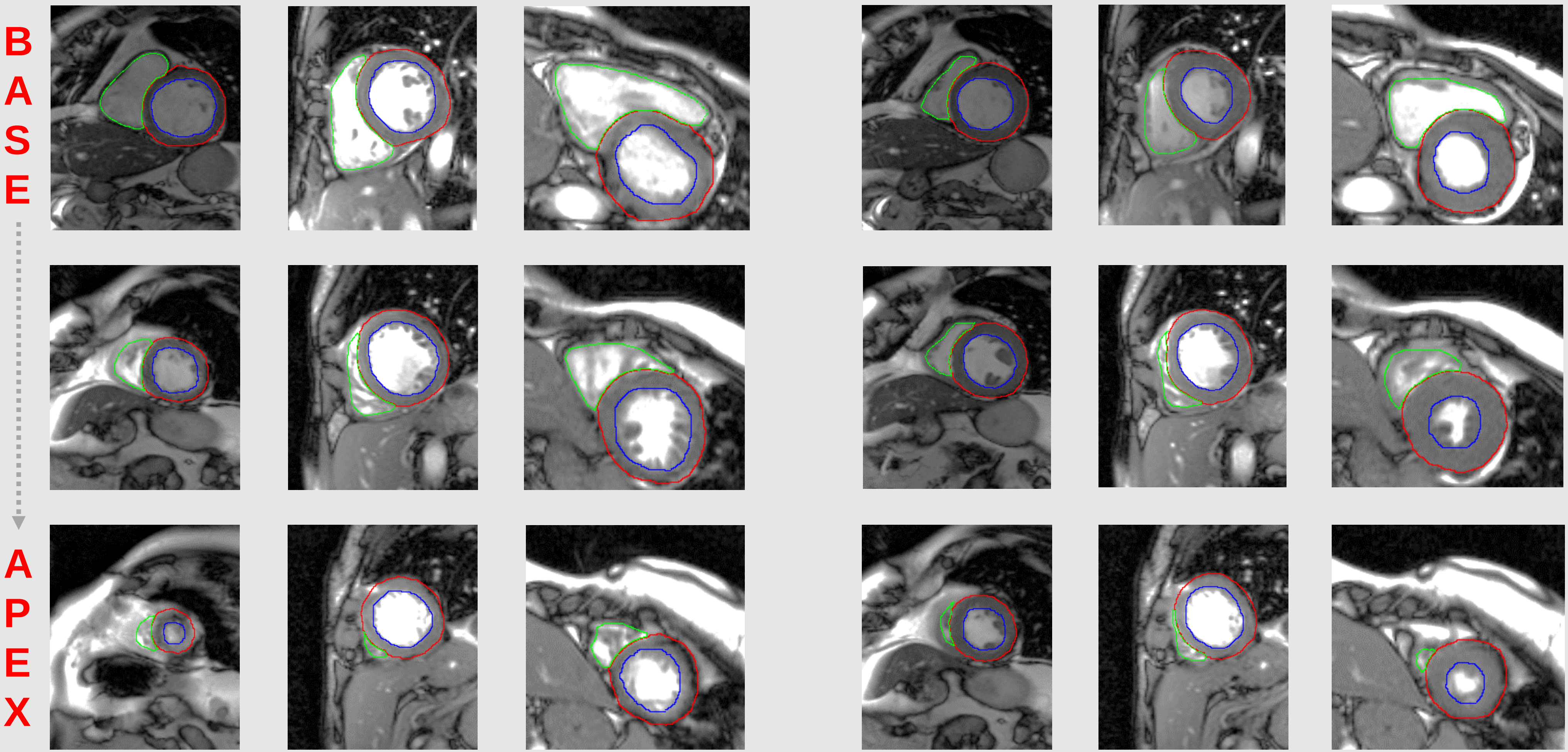
- Cardiovascular diseases:
  - A major cause of death in many countries *[Roger et al, 2012]*
  - **MRI** is a good tool to assess the cardiac contractile funtion



The aim is to compute the ventricle volume, the wall thickness…

Context

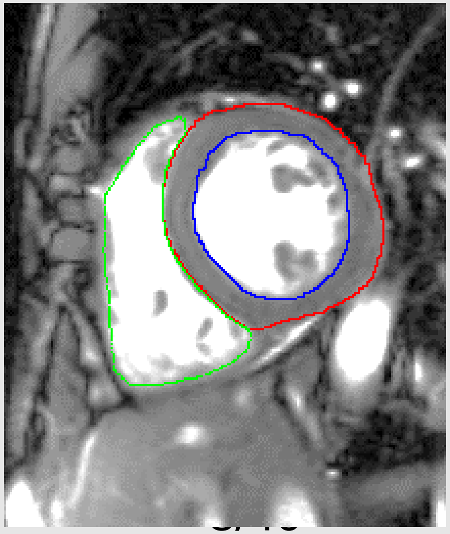
- Cardiac ventricle segmentation: a challenging task



Context

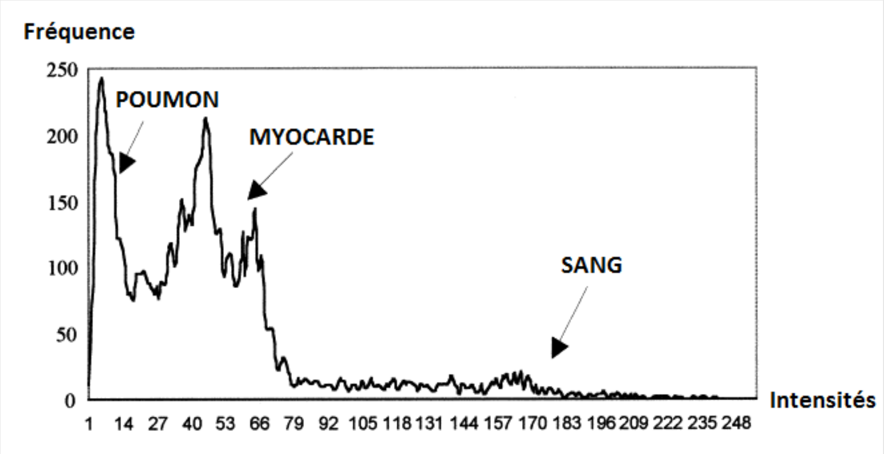
- In clinical routine:
- Manual segmentation:
  - Long and tedious task (20 minutes per patient)
  - Prone to intra and inter expert variabilities

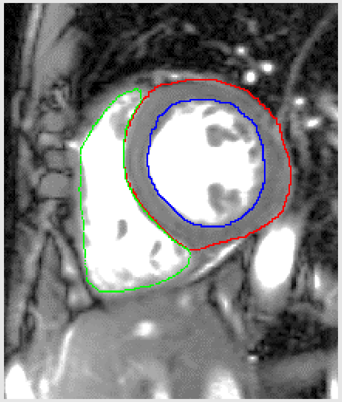
- Many research efforts
  - Some software tools exist especially for the LV
  - Problems remain for the right ventricle (RV)



Related works
cardiac image segmentation

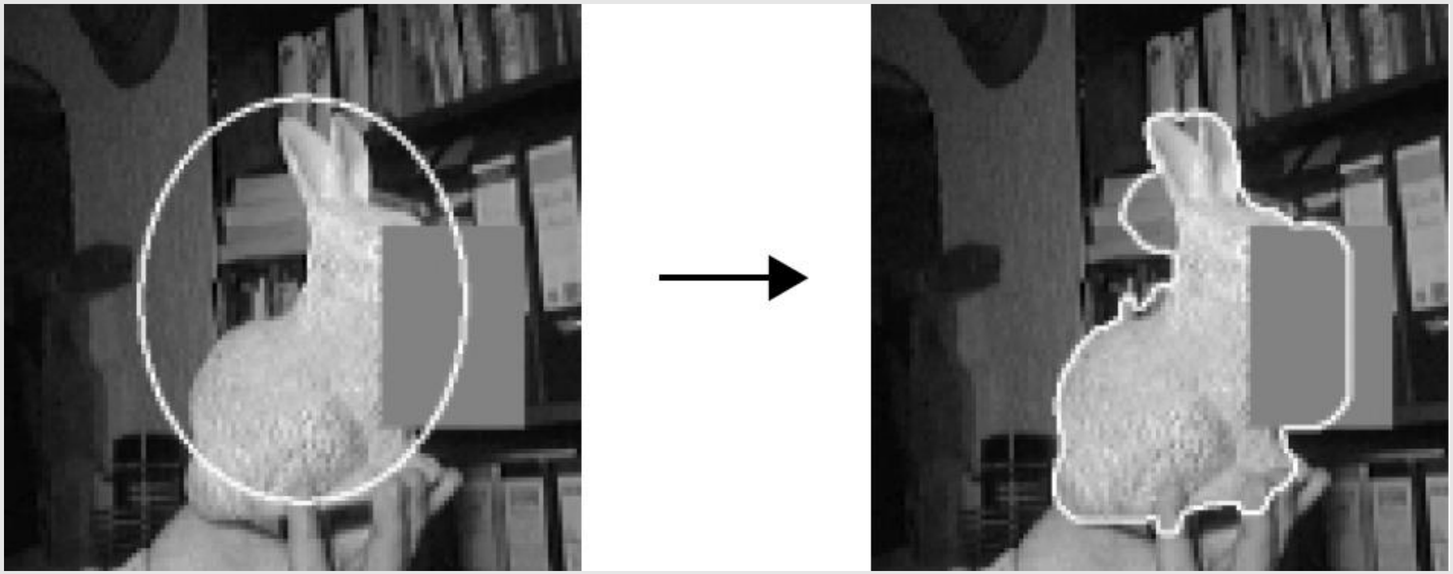
- Pixel-based methods: dedicated method
  - Thresholding, active contours, mathematical morphology…





- Prior information will help/constrain the segmentation in noisy, fuzzy image, or image with occlusions
  - Example : shape of the ventricle

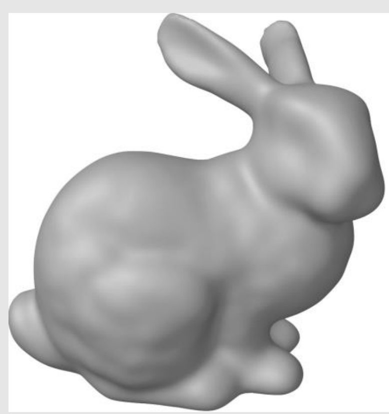
Related works
segmentation with shape prior



Without prior

With prior

Suppose I have
a bunny model…



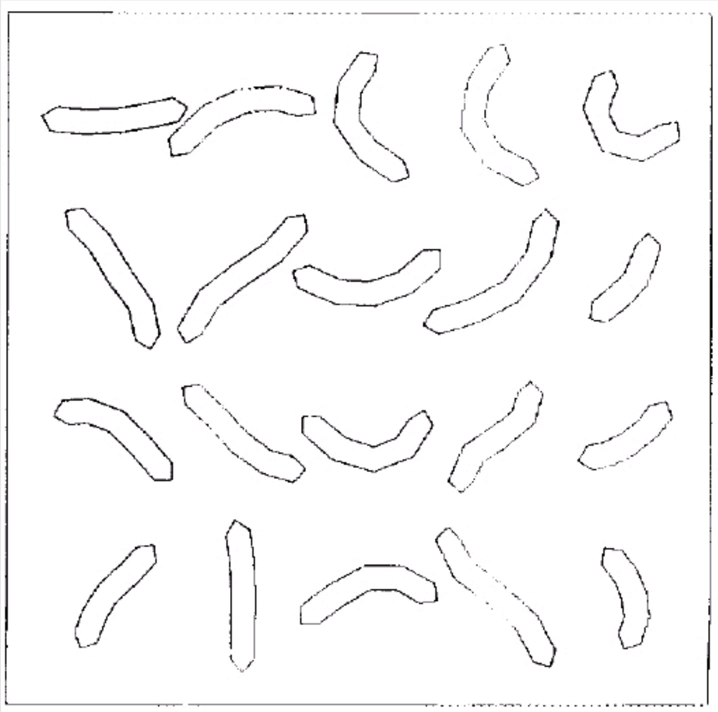
In 2D: a binary
map

Image segmentation with shape prior

Several ways to do it *(I'll present the 3 main ways)*

1) Active Shape Models (Cootes 1995)

- Assumes that you have a dataset of representative contours of the shape



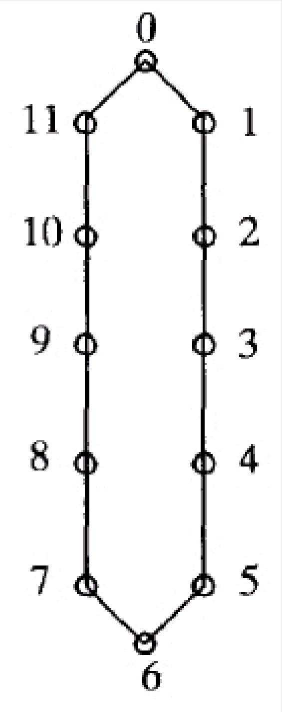
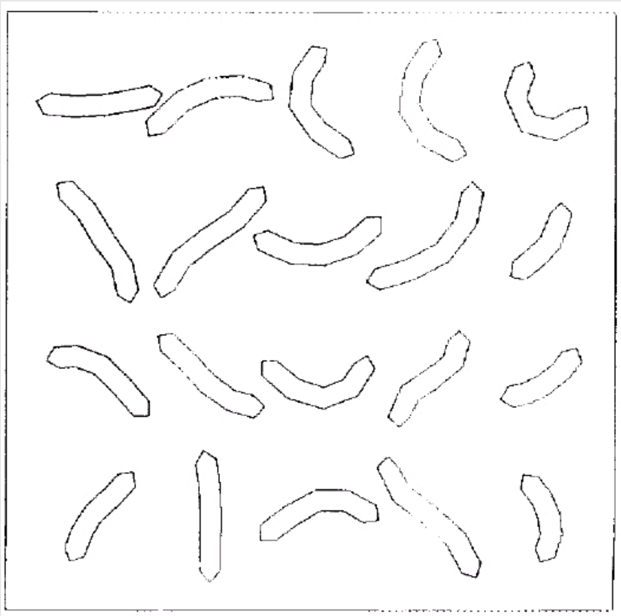
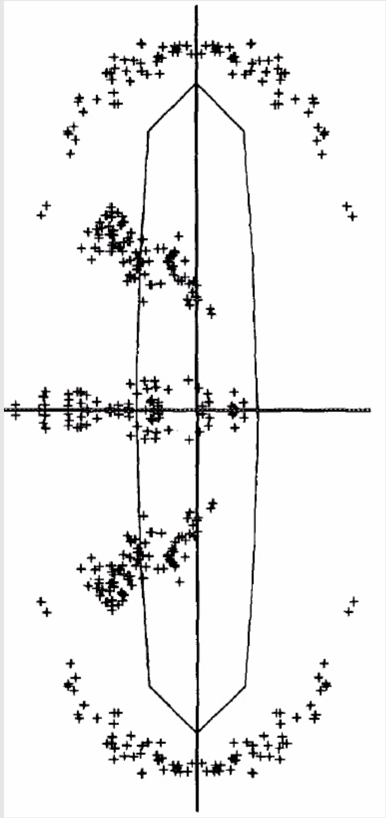


Image segmentation with shape prior

1) Active Shape Models (Cootes 1995)

- Assumes that you have a dataset of representative contours of the shape
  - Align all shapes





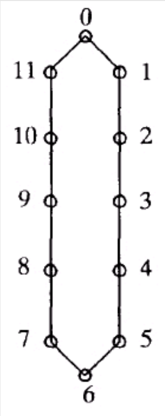
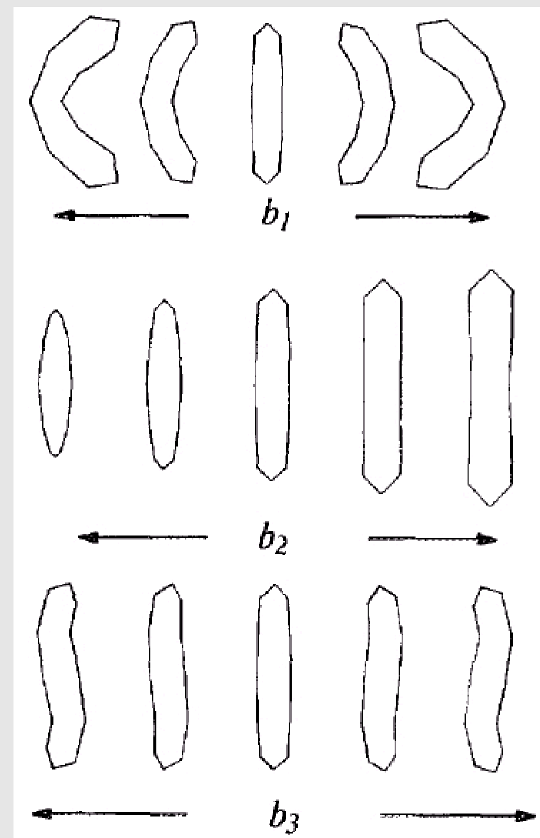


Image segmentation with shape prior

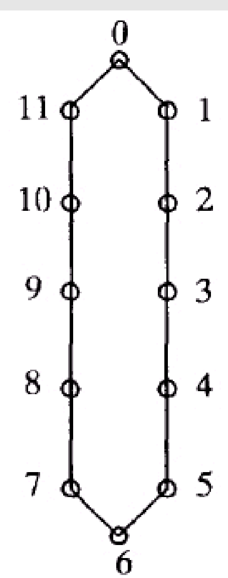
1) Active Shape Models (Cootes 1995)

- From the set of aligned shapes, you can compute
  - an average shape
  - a PCA on the contour points



Thus you get the major variability axis of the shape set

(called a Point Distribution Model (PDM))



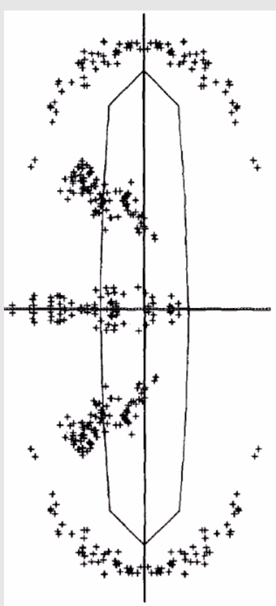
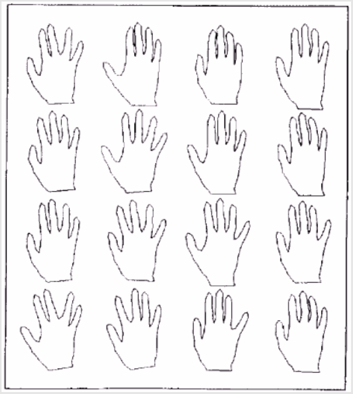


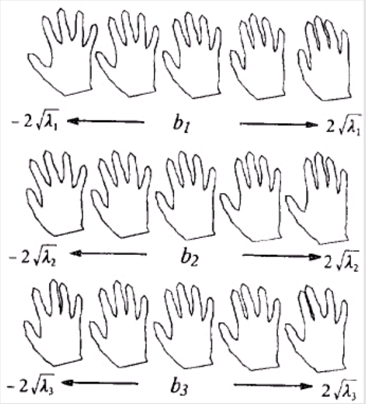
Image segmentation with shape prior

1) Active Shape Models (Cootes 1995) (ASM–AAM)

- Once you have the an average shape and the way shapes usually vary
  - → Use the PDM for segmentation with deformable models
  - → The segmentation result is constrained to lie within the major variabilities axis

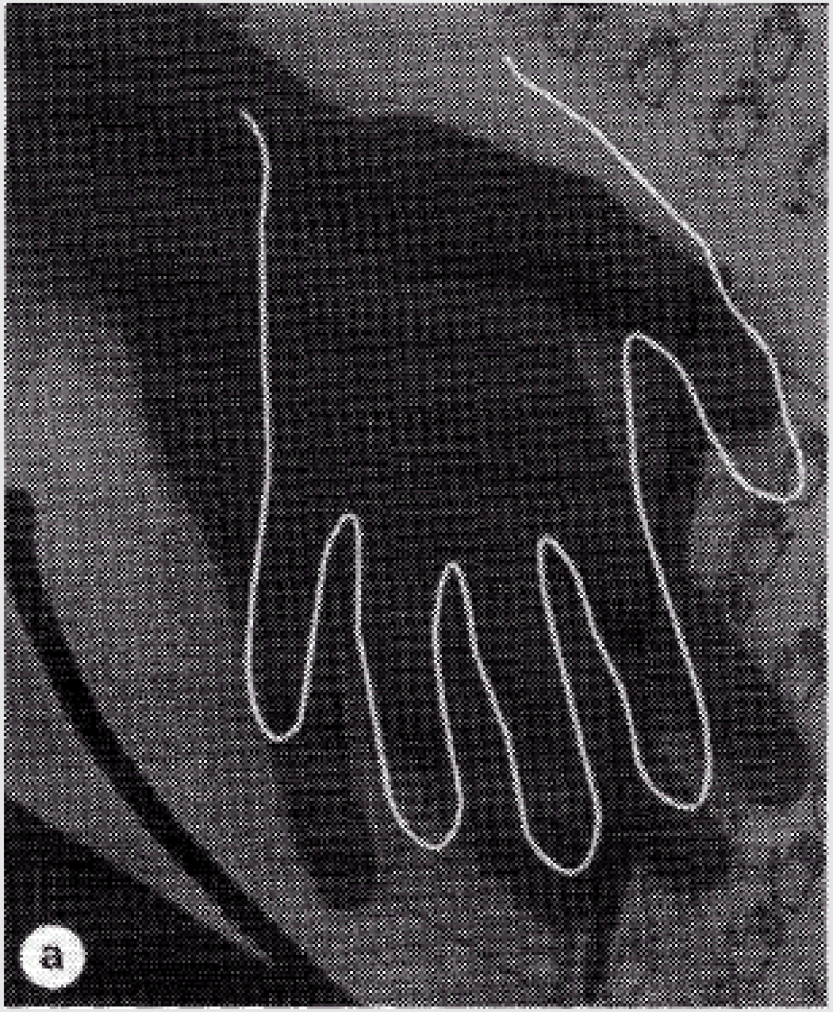
Example:
(72 points)





ASM : segmentation

- Initialization



ASM : segmentation

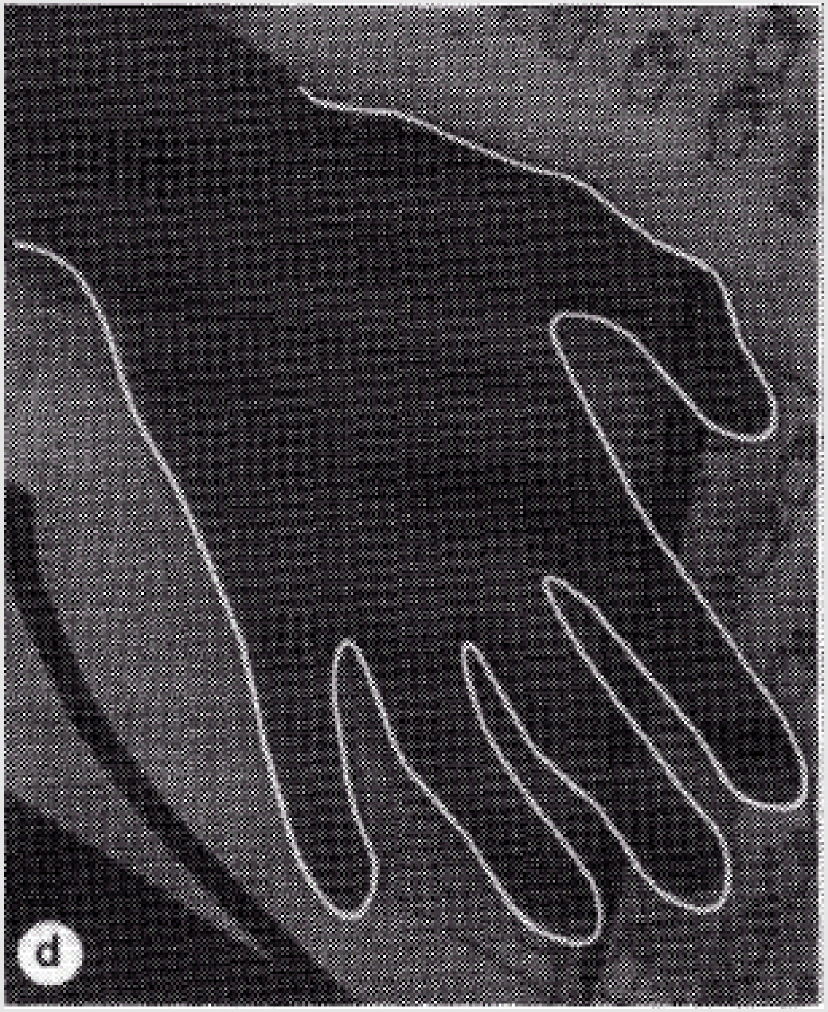
- 100 iterations

ASM : segmentation

- 200 iterations

ASM : segmentation

- 350 iterations



Problem: What if the shape to be segmented does noe lie within the dataset variability?

Other issue: point labelling can be very tedious

Image segmentation with shape prior

2) Segmentation may be considered as a minimization problem (eg active contours, graph cut…):

S = arg max D(S) + R(S) + P(S)

S is the segmentation (binary map, contour points)

Data-driven term (eg, based on image gradient, on histogram of the object/background….)

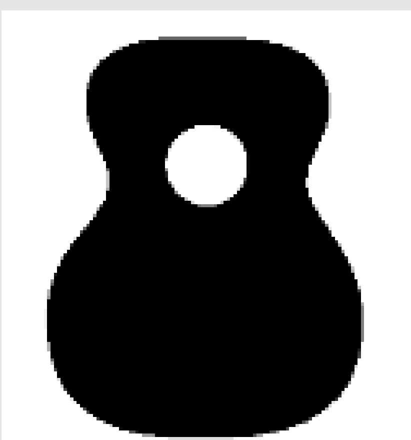
Regularization term (eg, smoothness and geometric properties on the contour….)

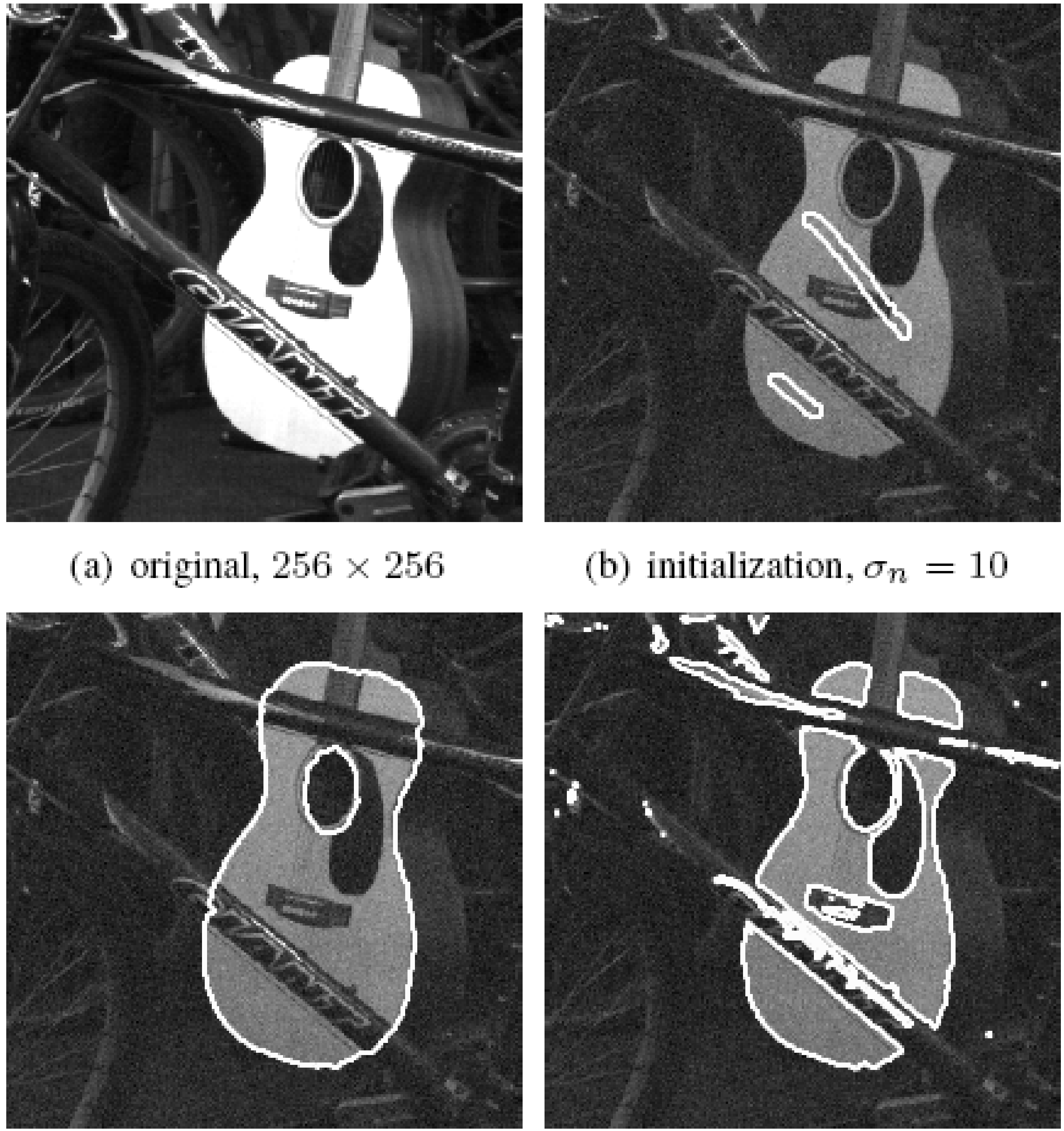
Shape prior term

Very simple example with Prior being a binary map:

$$P(S) = \sum_{all\ pixels\ p} (S(p) - Prior(p))^2$$

Vu, CVPR08





(a) original, 256×256

(b) initialization, $\sigma_n = 10$

(c) SP, 18 iter, 3.036 sec.

(d) no SP

Image segmentation with shape prior

2) Problem: How to register the shape model to the image?

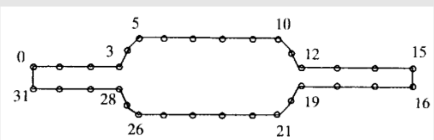
A usual solution is to proceed iteratively:

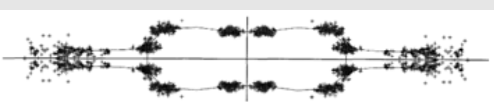
Alternate between model position estimation & segmentation…

How to represent the shape model?

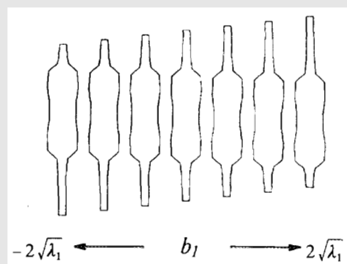
Explicit representation

PDM *[Cootes et al, 1995]*





PCA

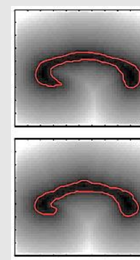


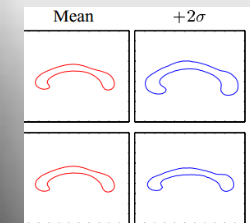
- *Labelling the data with corresponding points is quite tedious*

Implicit representation

Signed Distance Function

[Leventon et al, 2000]





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- E

Image segmentation with shape prior

3) Registration-based segmentation (single atlas)

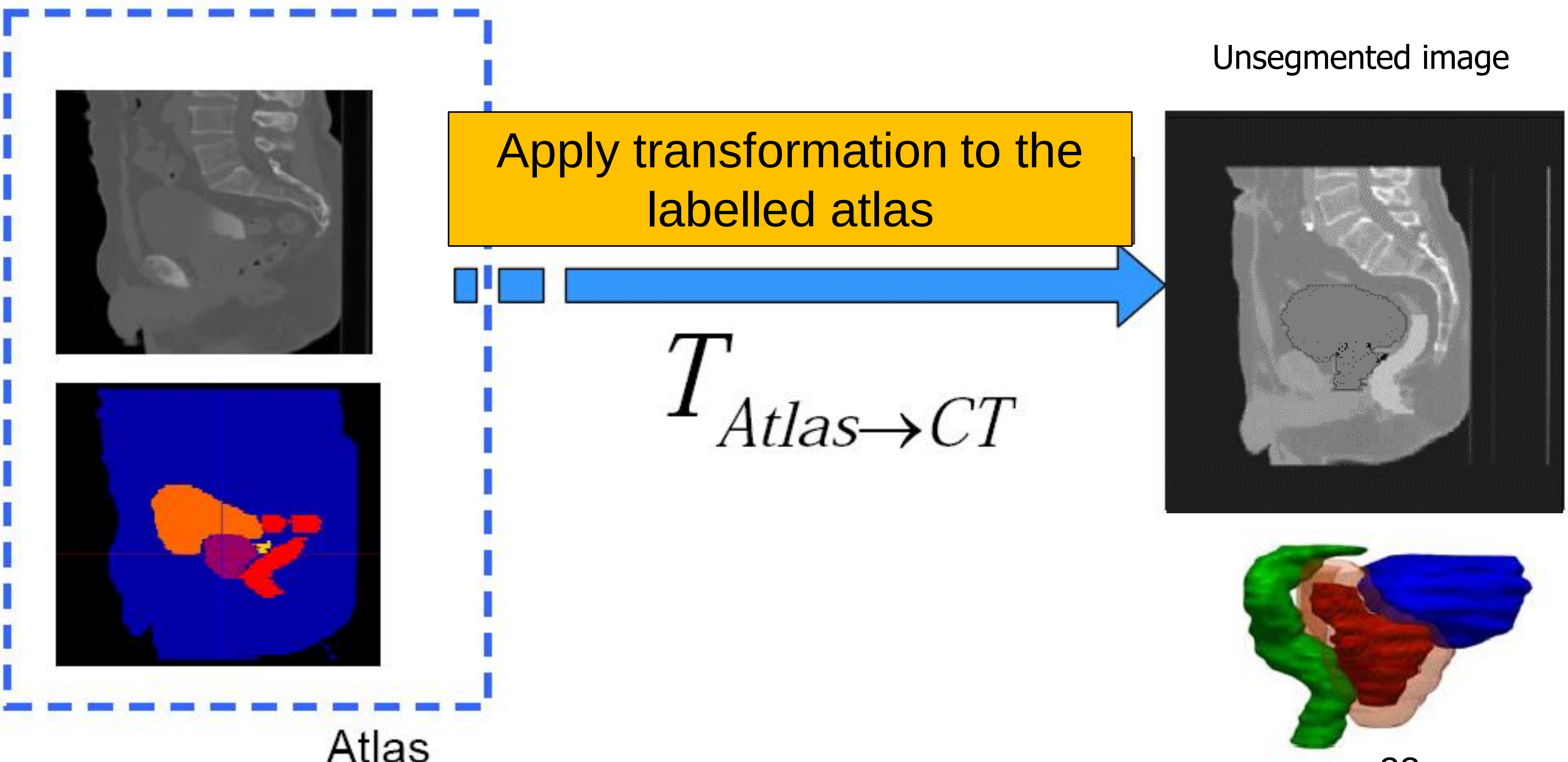


Image segmentation with shape prior

3) Registration-based segmentation (multiple atlases)

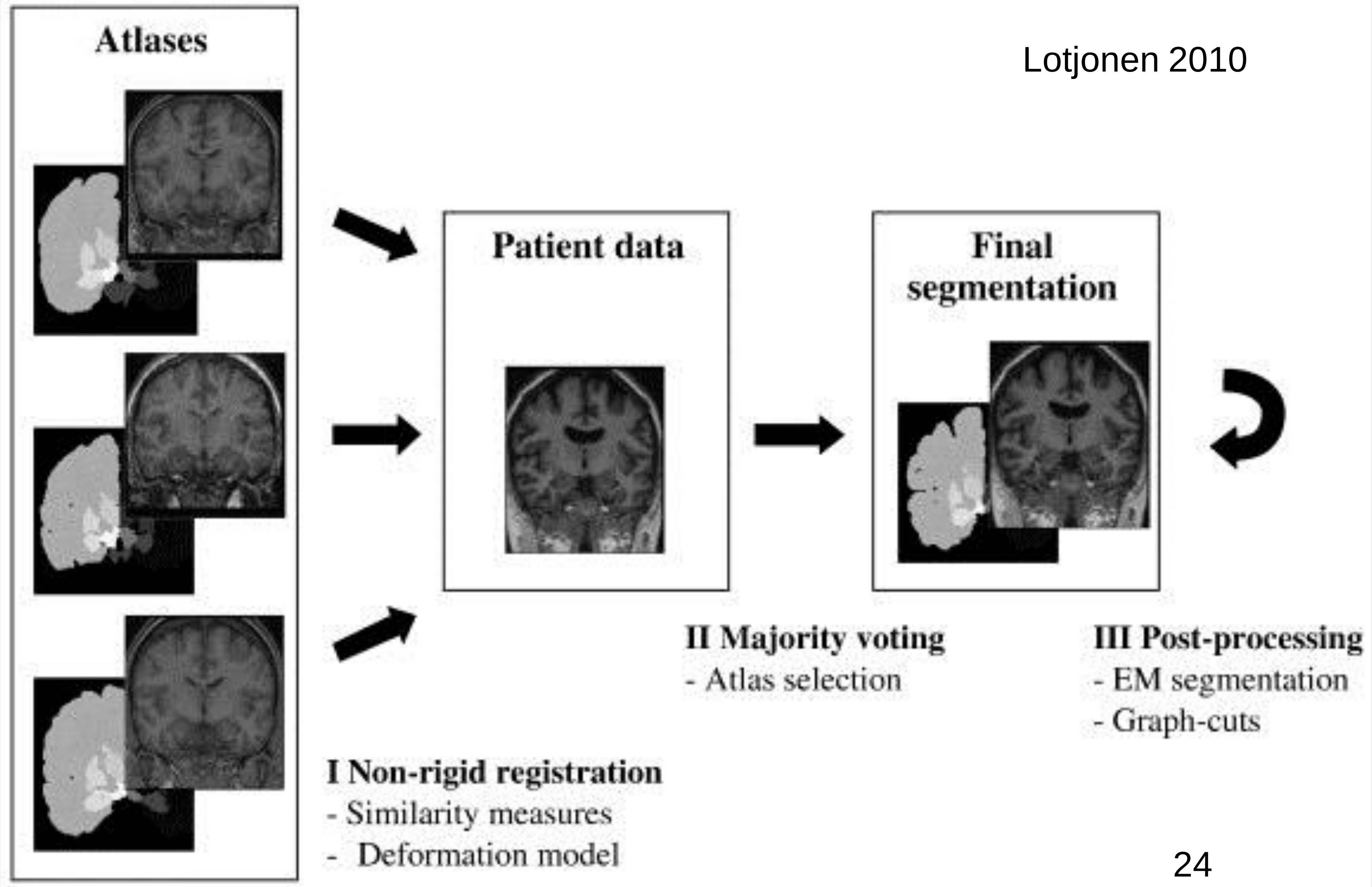


Image segmentation with shape prior

3) Registration-based segmentation (multiple atlases)

Another example of local label fusion:

For each pixel x, compute the probability to have label l:

$$P(L(x) = l | L'_n(x), I(x), I'_n(x)) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{[I(x)-I'_n(x)]^2}{2\sigma_i^2}} \cdot \delta_{l,L'_n(x)}$$

$L'_n(x)$ and $I'_n(x)$: label and intensity of atlas n

$$L(x) = \arg max \sum_{all\ atlases\ n} P(L(x) = l | L'(x), I(x), I'_n(x))$$

We also want adjacent pixels to x to have an opinion of the label of x!

$$P(L(x) = l | L'_n(x+\Delta x), I(x), I'_n(x+\Delta x))$$
$$= \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{[I(x)-I'_n(x+\Delta x)]^2}{2\sigma_i^2}} \cdot \frac{1}{\sqrt{2\pi}\sigma_d} e^{-\frac{D(\Delta x)^2}{2\sigma_d^2}} \cdot \delta_{l,L'_n(x+\Delta x)}$$

Image segmentation with shape prior

3) Registration-based segmentation (multiple atlases)

Issues: Segmentation results heavily relies on the registration quality

How to chose the optimal number of atlases?

Our approach

•**RV segmentation**: image intensity alone is not enough, requires prior shape information

- ➔ Collaboration with Rouen University Hospital (Radiology Dept)
- ➔ Cardiac radiologists have provided us with 48 MRI exams with segmented RV (around 750 images)

Construction of a shape model for the design of our RV segmentation method

Organization of a segmentation competition in Oct'12 (MICCAI workshop)

Our approach

- Our aim is to:
  - Construct a shape model, based on the manual segmentations
  - Use this model in a minimization based segmentation framework

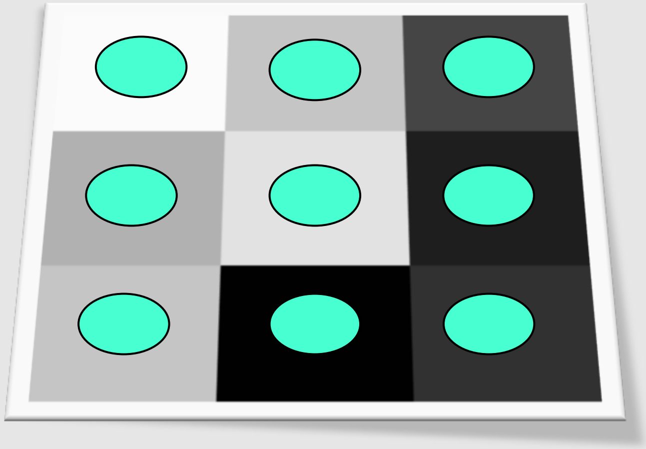
- We chose the **graph cuts approach** (GC) *[Boykov et Jolly, 2001]*
  - The global minimum of the energy function is guaranteed
  - The framework is versatile enough to incorporate
  - Complexity in 2D is very low

Graph cut: basic principle

Consider the observation field y_i (the image)

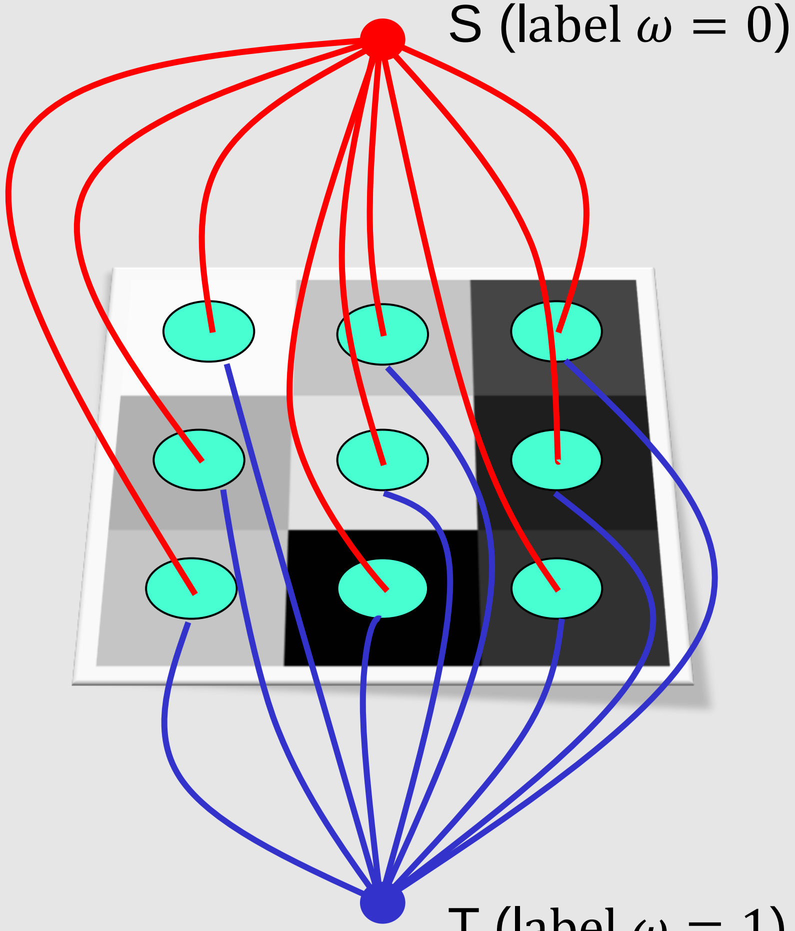
Graph cut: basic principle

- Each pixel is considered as a node



Graph cut: basic principle

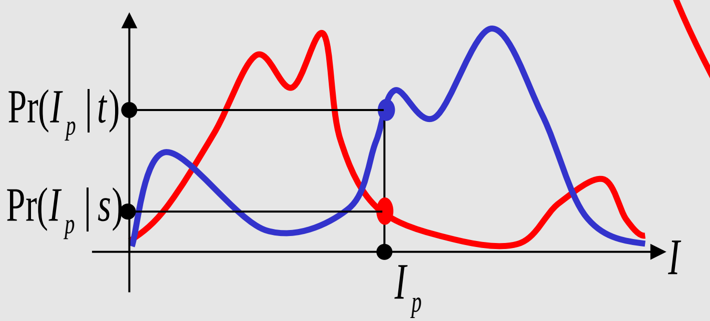
Consider binary segmentation.



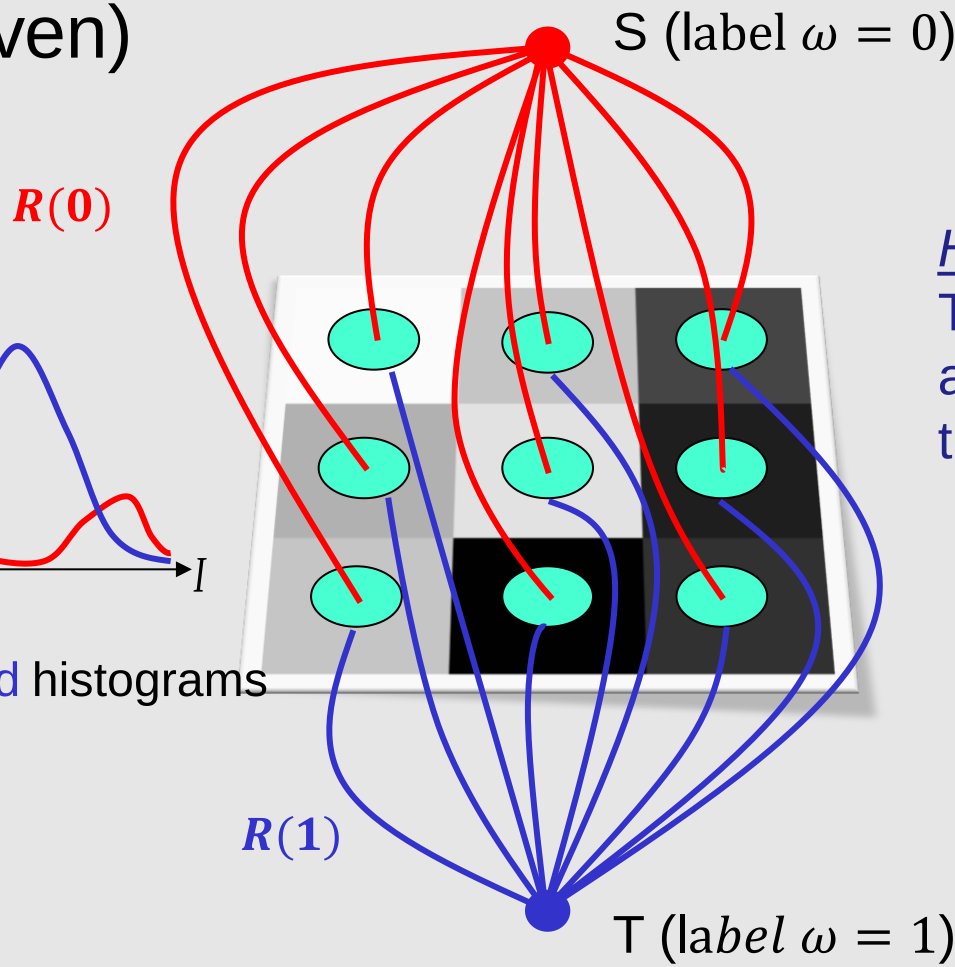
We introduce 2 special nodes **S and T**, linked to the pixels
→ t-links

Graph cut: basic principle

- Links are weighted with a region-based term $R_i(\omega)$ (data-driven)



object / background histograms

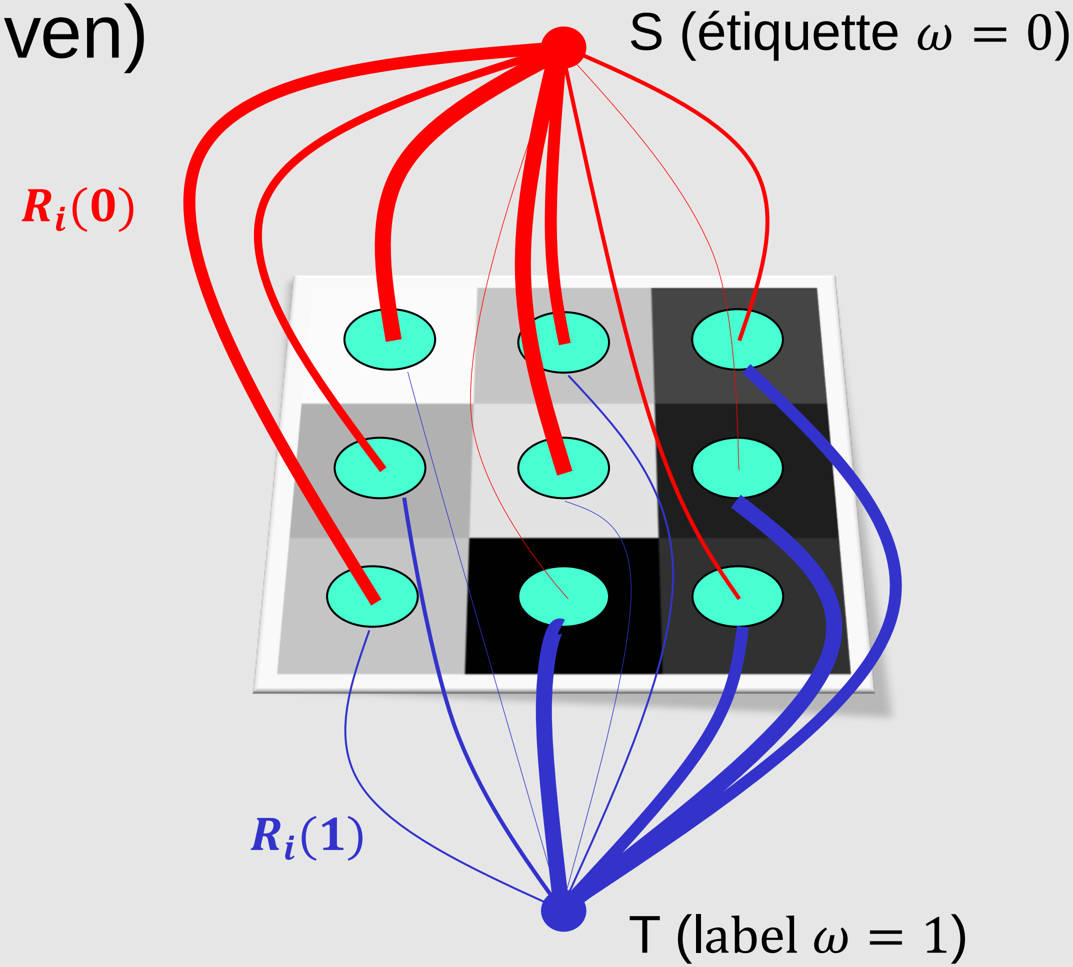


How to design Ri ?
The more similar the pixels are to S or T, the stronger the t-links

$$R_i(S) = -\ln \Pr(y_i|T)$$
$$R_i(T) = -\ln \Pr(y_i|S)$$

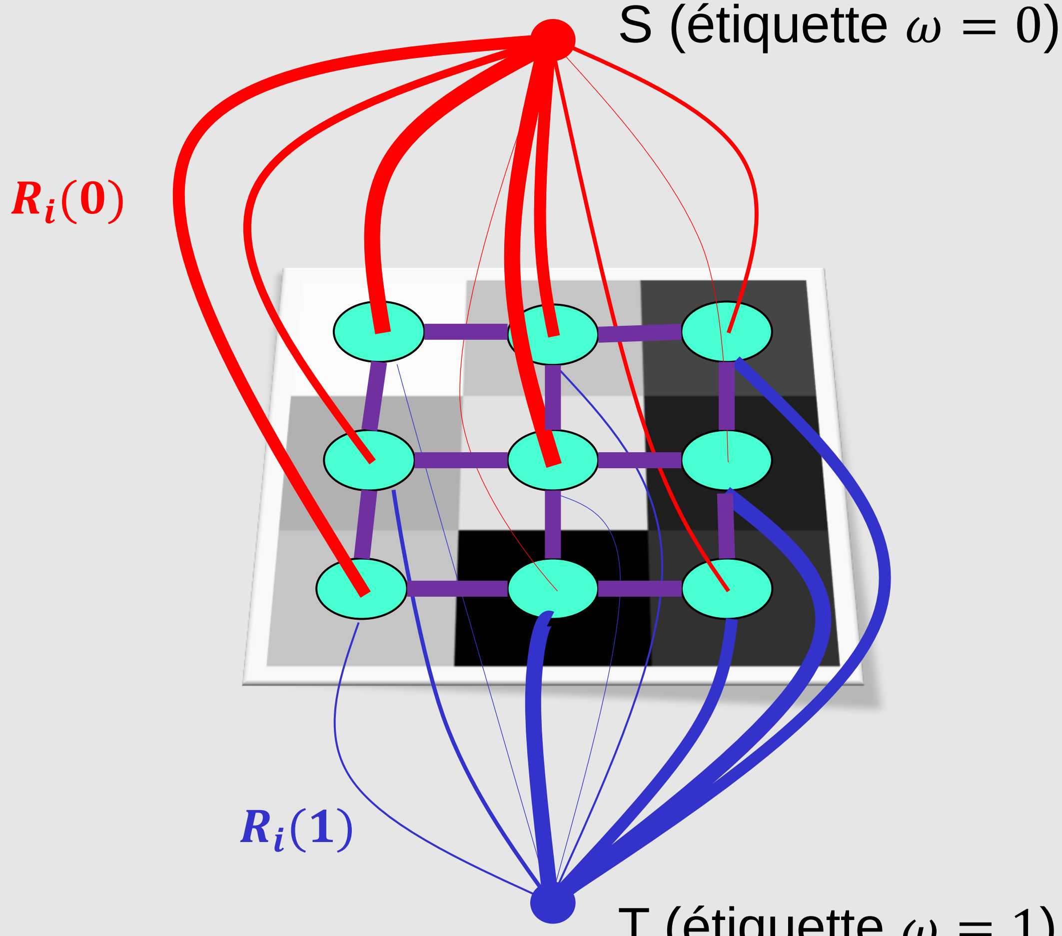
Graph cut: basic principle

- Links are weighted with a region-based term $R_i(\omega)$ (data-driven)



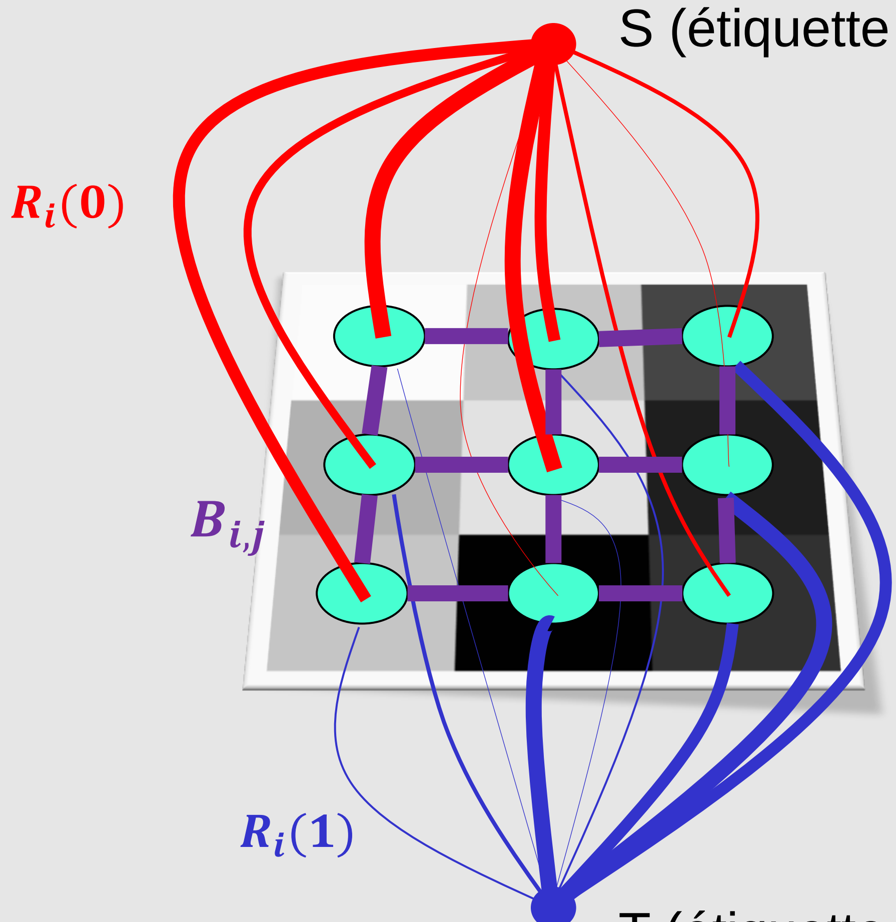
Graph cut: basic principle

- Let's add a link between neighboring pixels: n-links



Graph cut: basic principle

- N-links are weighted by a regularization term $B_{i,j}$

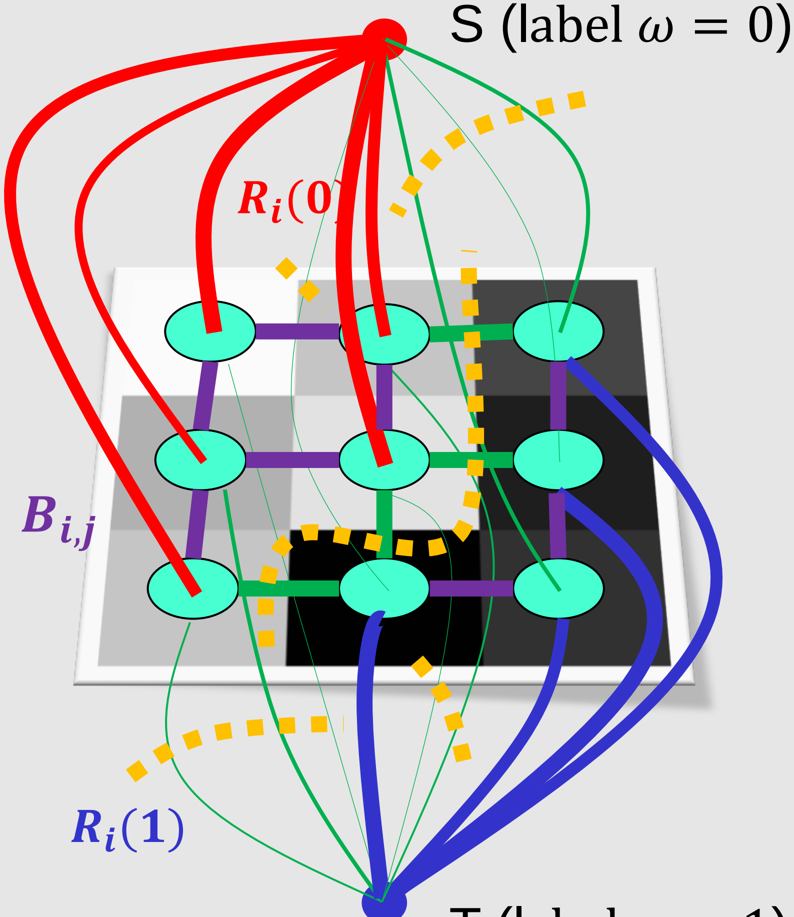


How to design Bij ?
The more similar the pixels (in terms of grey levels), the stronger the n-link

$$B_{i,j} = \exp\left\{-\frac{(y_i - y_j)^2}{2\sigma^2}\right\}$$

Graph cut: basic principle

To obtain a segmentation (= a labelling), the graph is cut



The nodes are divided into 2 groups, one contains the source and the other the sink.

Cost function associated to a cut:

$$E(L) = \sum_i R_i(L_i) + \lambda \sum_{i,j \in N} B_{i,j} \, . \, \delta(L_i \neq L_j)$$

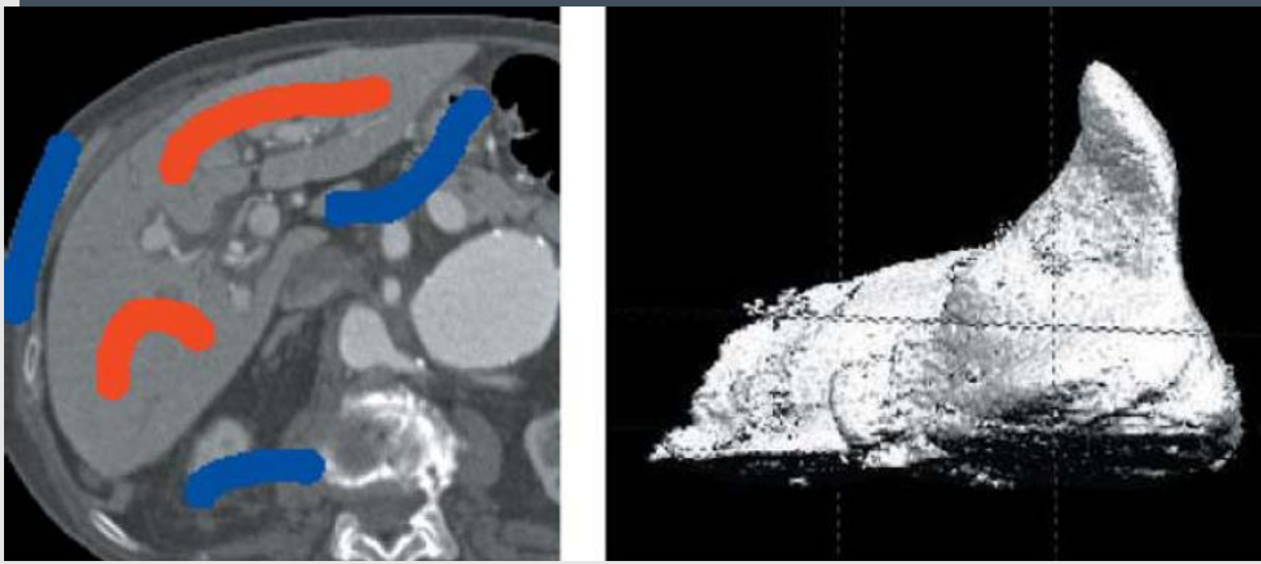
The **best** segmentation is obtained when E(L) is minimum

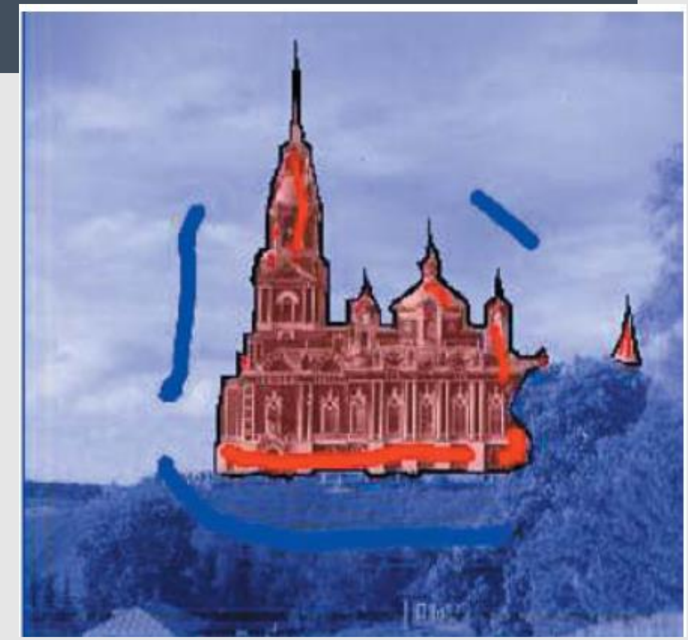
But how to get L such that E(L) is minimum?

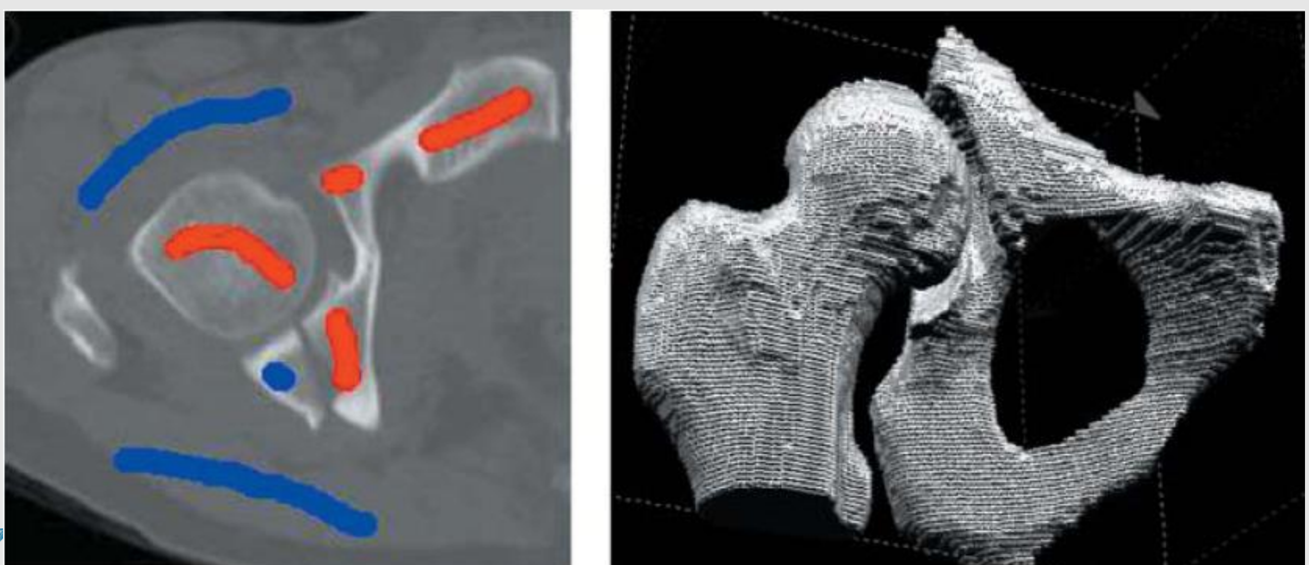
→ **Use optimization algorithm called min-cut max-flow** *[Boykov & Kolmogorov, 2004]*

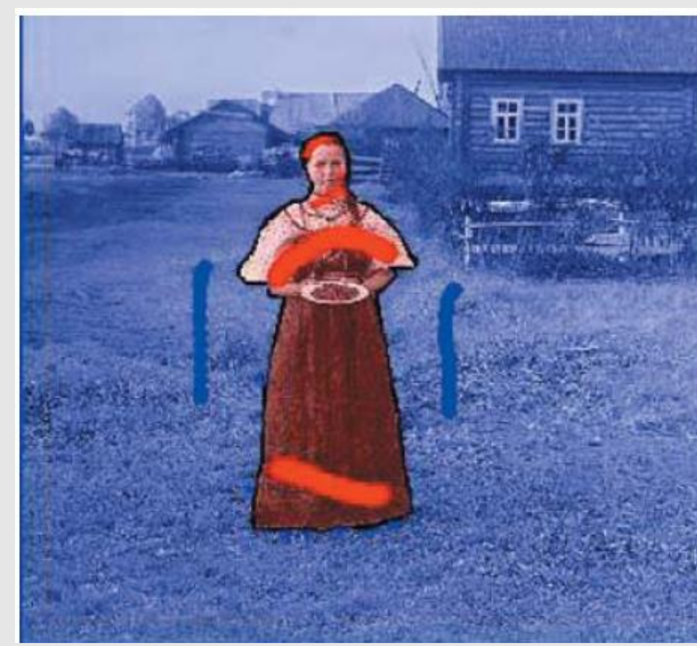
We have just seen binary segmentation…
The framework has been extended to multi-label segmentation

GC used as an interactive segmentation tool









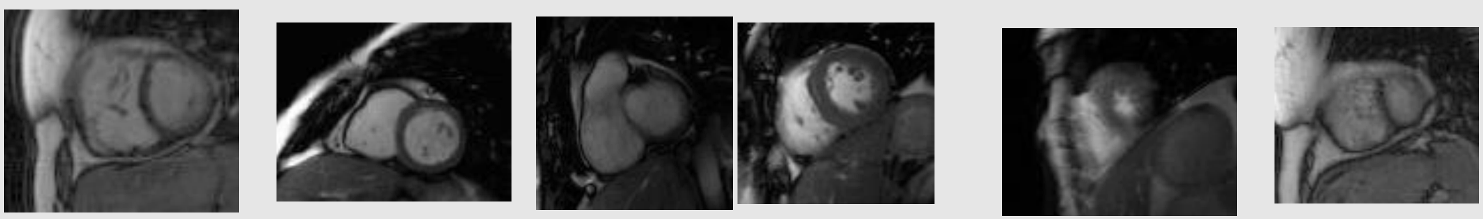
Boycov, IJCV, 2006

A word on GrabCut…

- Variant of Graph Cut: Interactive Foreground Extraction using Iterated Graph Cuts

Back to our problem…

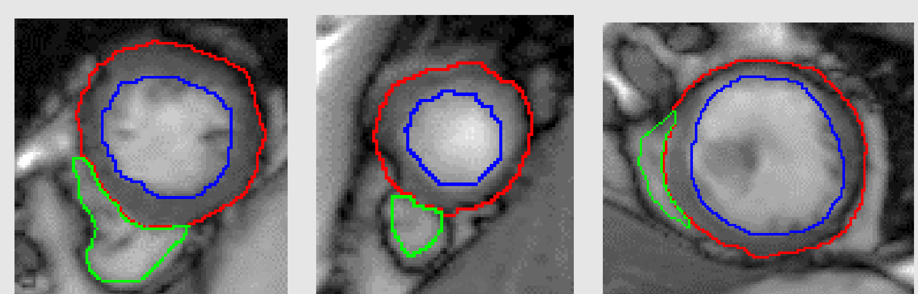
- We want to automatically segment the cardiac ventricles in MR image where borders are not well defined and ventricles shapes are highly variable



- We construct a shape model from manually labelled data

No anatomical landmarks

→ We use the Signed Distance Function representation for our shape model



Back to our problem…

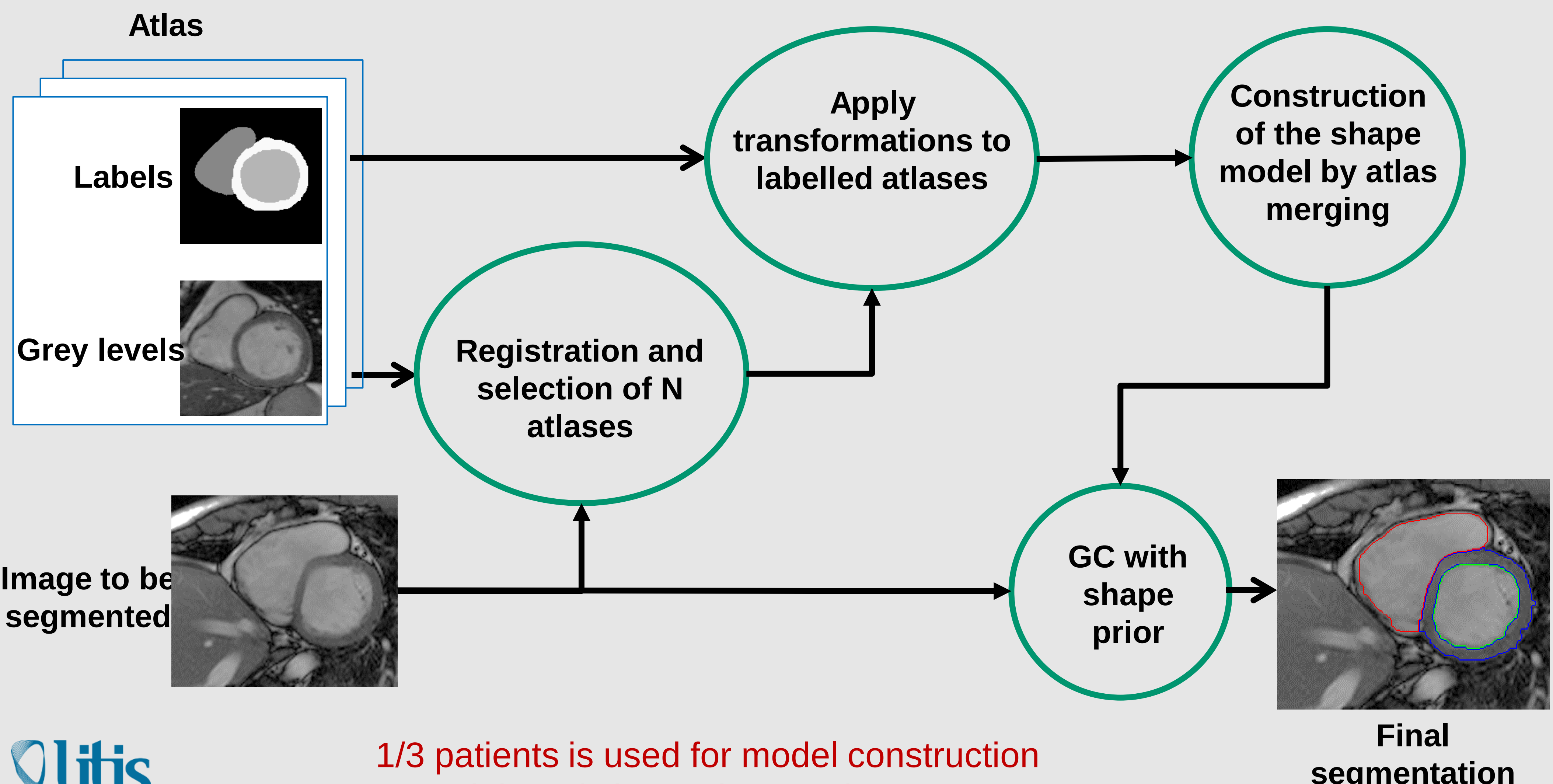
- We use the model within the GC framework:
- We design the graph cost function as:

$$E(L) = \sum_{i} R_i(L_i) + \sum_{i} P_i(L_i) + \lambda \sum_{i,j \in N} B_{i,j} \,.\, \delta(L_i \neq L_j)$$

Additional term linked to the shape prior

Our GC based approach with shape prior

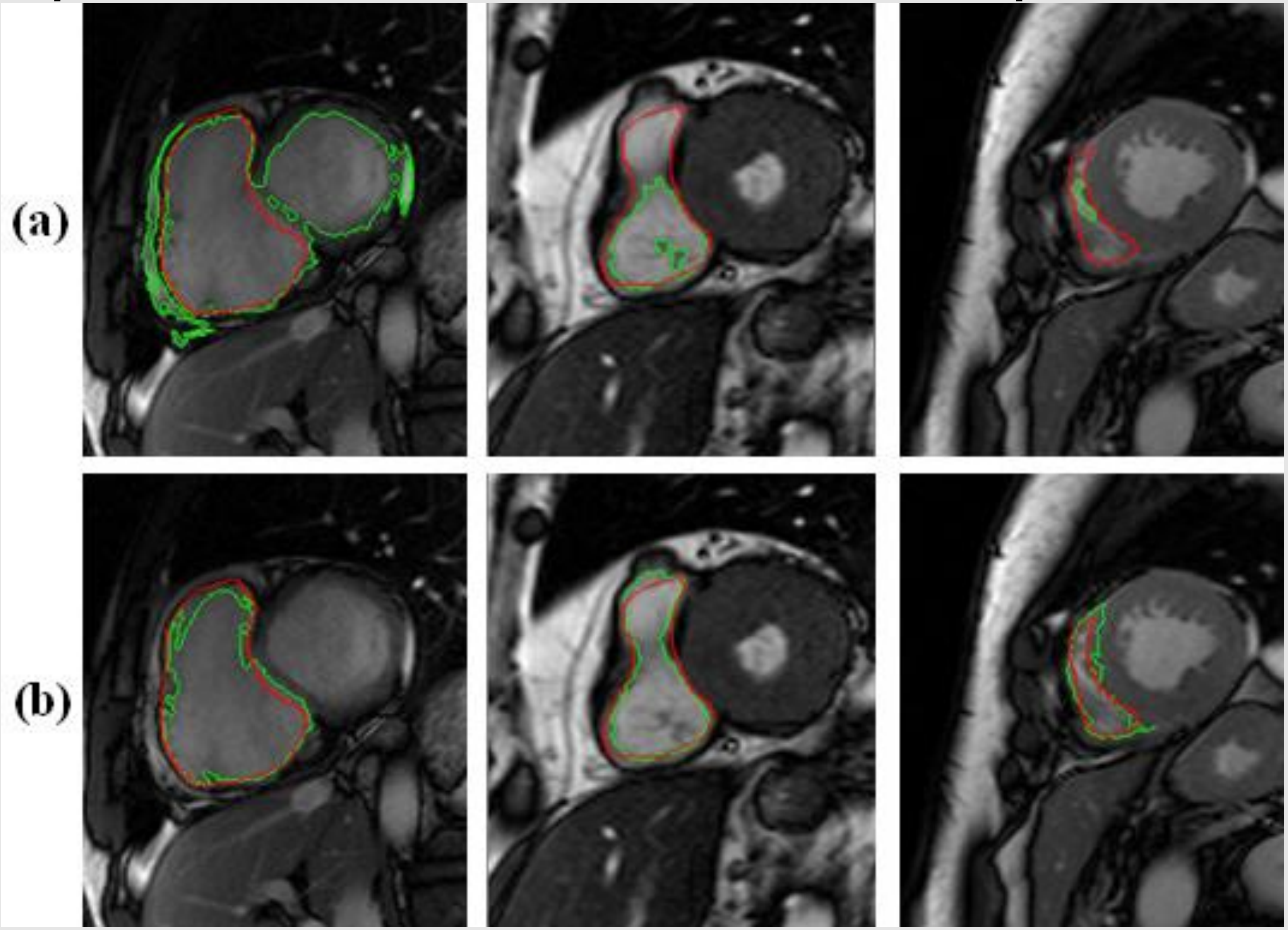
- Overview:

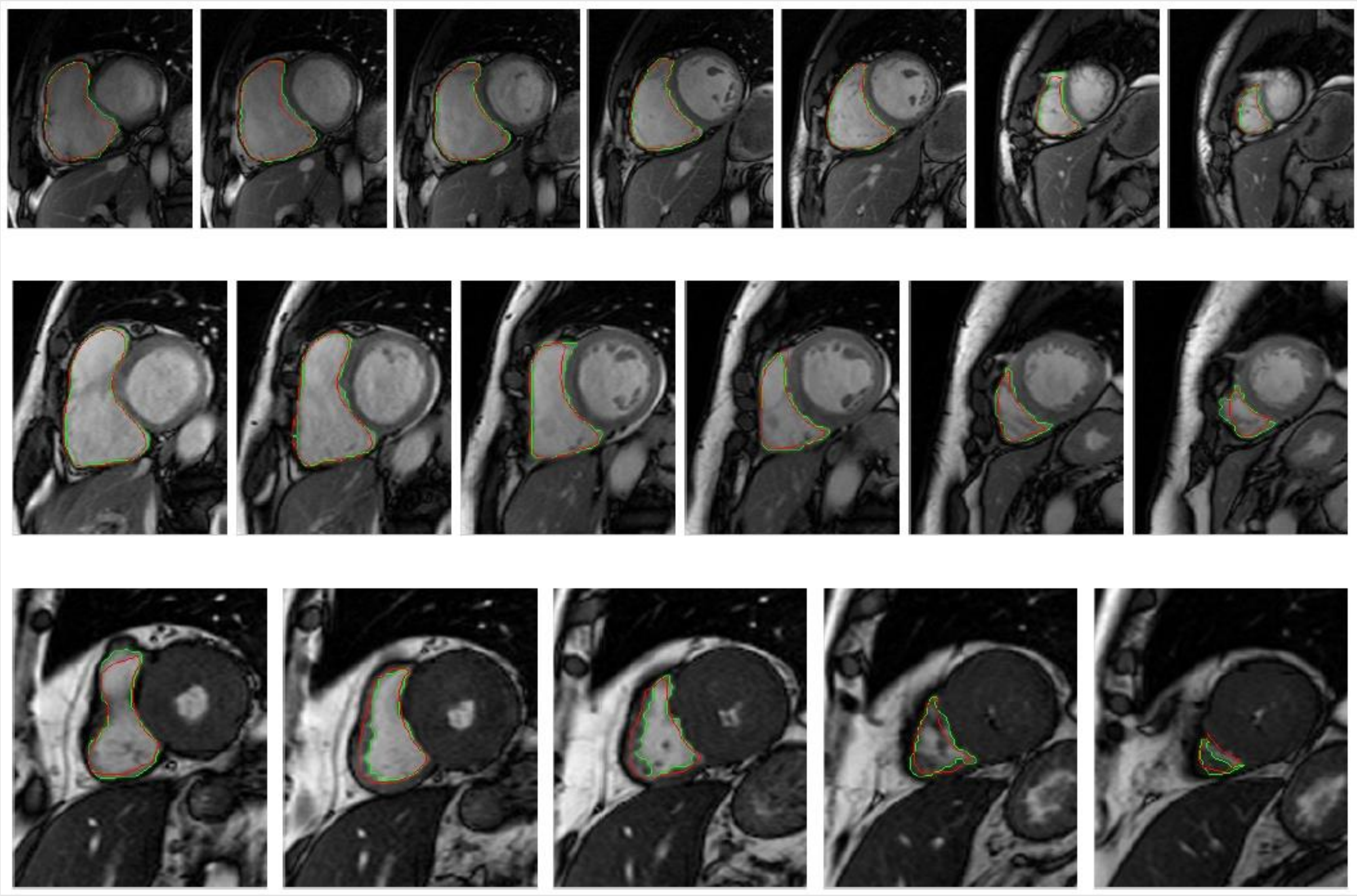


1/3 patients is used for model construction
Remaining 2/3 is used for testing

A few results

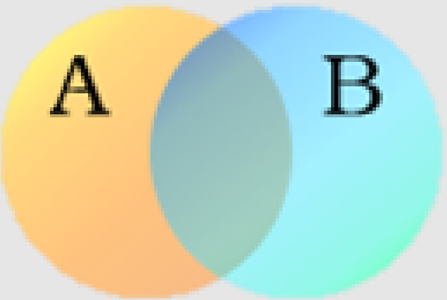
- Comparaison without and with an a priori





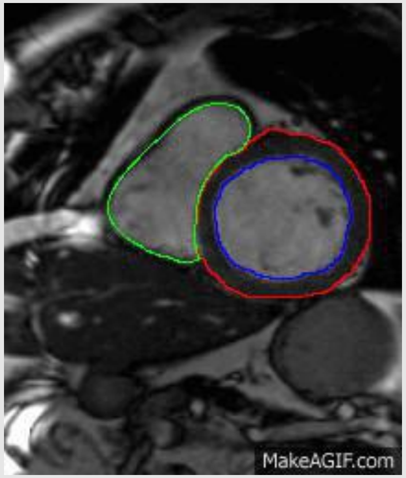
Some quantitative results

- Comparison of manual contours and automated contours with the Dice metric:
  - Overlap measure $D(\boldsymbol{A}, \boldsymbol{B}) = \dfrac{2|\boldsymbol{A} \cap \boldsymbol{B}|}{|\boldsymbol{A}| + |\boldsymbol{B}|}$

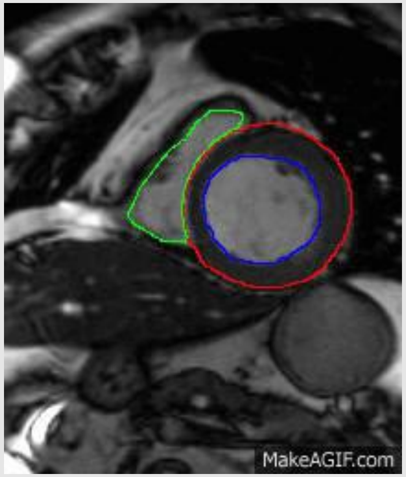


	ED	ES
RV (red)	0.87 ± 0.06	0.73 ± 0.16
LV (cyan)	0.95 ± 0.03	0.80 ± 0.26
Myocardium (blue)	0.81 ± 0.08	0.77 ± 0.19

ED (dilatation)



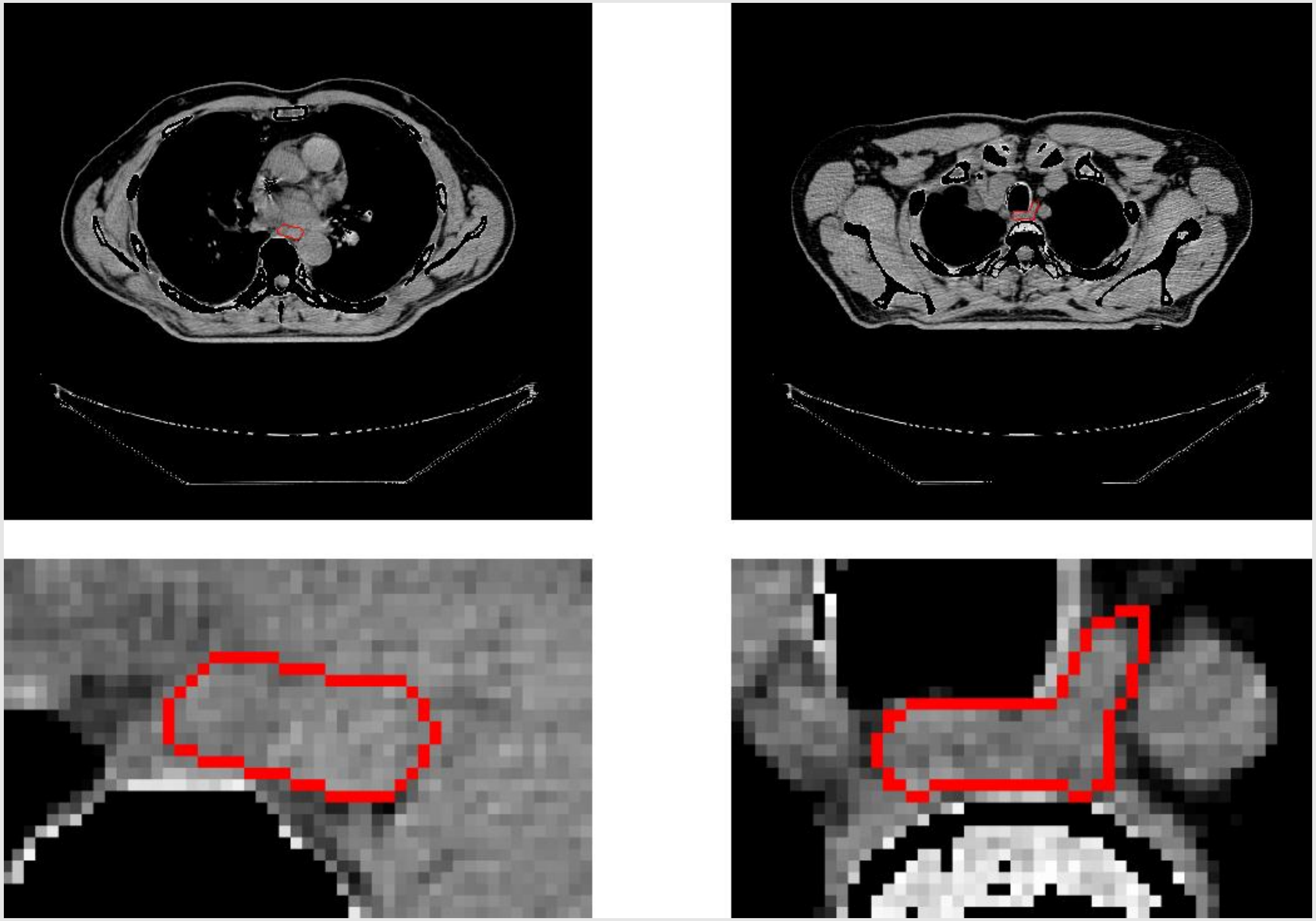
ES (contraction)



  - One of the best results in our RVSC challenge …

Perspectives

- Application to some other segmentation contexts (3D)



Associated publications

- **Our prior-based segmentation approach applied to RV:**
  - Grosgeorge, D., Petitjean, C., et Ruan, S. (2014). Joint Segmentation of Right and Left Cardiac Ventricles Using Multi-Label Graph Cut. ***IEEE ISBI***, Beijing, Chine.
  - Grosgeorge, D., Petitjean, C., Dacher, J. N., et Ruan, S. (2013). Graph cut segmentation with a statistical shape model in cardiac MRI*. **CVIU***, 117(9), 1027-1035.
  - Grosgeorge, D., Petitjean, C., Ruan, S., Caudron, J., et Dacher, J. N. (2012). Right ventricle segmentation by graph cut with shape prior. ***3D Cardiovascular Imaging : a MICCAI Segmentation Challenge***, Nice : France.
- **The Right Ventricle Segmentation challenge at MICCAI'12:**
  - C. Petitjean, M.A. Zuluaga, et al, Right Ventricle Segmentation From Cardiac MRI: A Collation Study, ***Medical Image Analysis***, in press, 2014
  - C. Petitjean, S. Ruan, D. Grosgeorge, J. Caudron, and J.-N. Dacher Right Ventricle Segmentation in Cardiac MRI: a MICCAI'12 Challenge. Proceedings of "3D Cardiovascular Imaging: a MICCAI segmentation challenge", Nice France, 2012.
- **A review of LV and RV segmentation methods:**
  - C. Petitjean and J.-N. Dacher, A review of segmentation methods in short-axis cardiac images, ***Medical Image Analysis***, vol. 15, pp. 169-184, 2011

Thank you!

- For listening…
- Any questions?