UNIVERSITÉ DE ROUEN

M2NUM

Plateforme haut-normande en Modélisation Mathématique: applications et simulations NUMériques pour les énergies renouvelables, l'éco-mobilité et l'imagerie

Image segmentation with a statistical shape prior

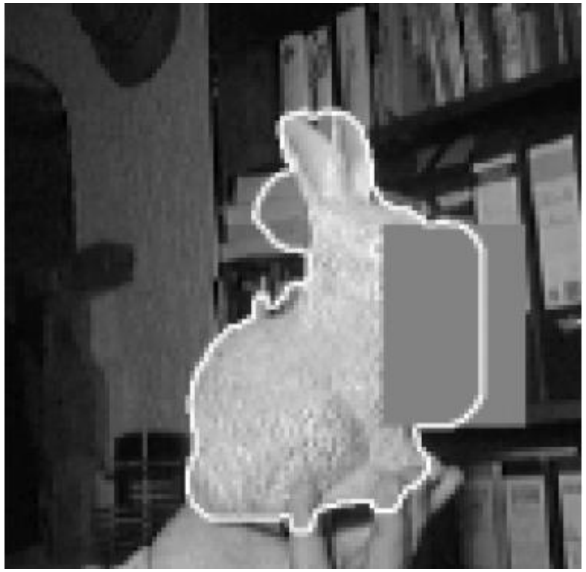
Caroline Petitjean

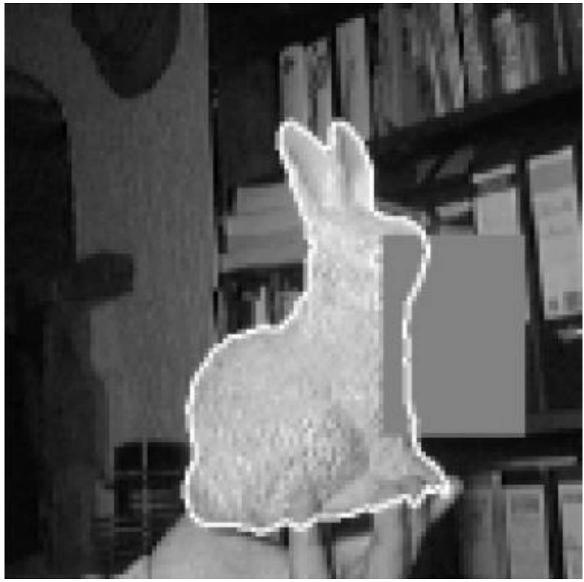
avec Arturo Mendoza Quispe

Journée Traitement d'images, 9 avril 2015

litis

Prior information based segmentation



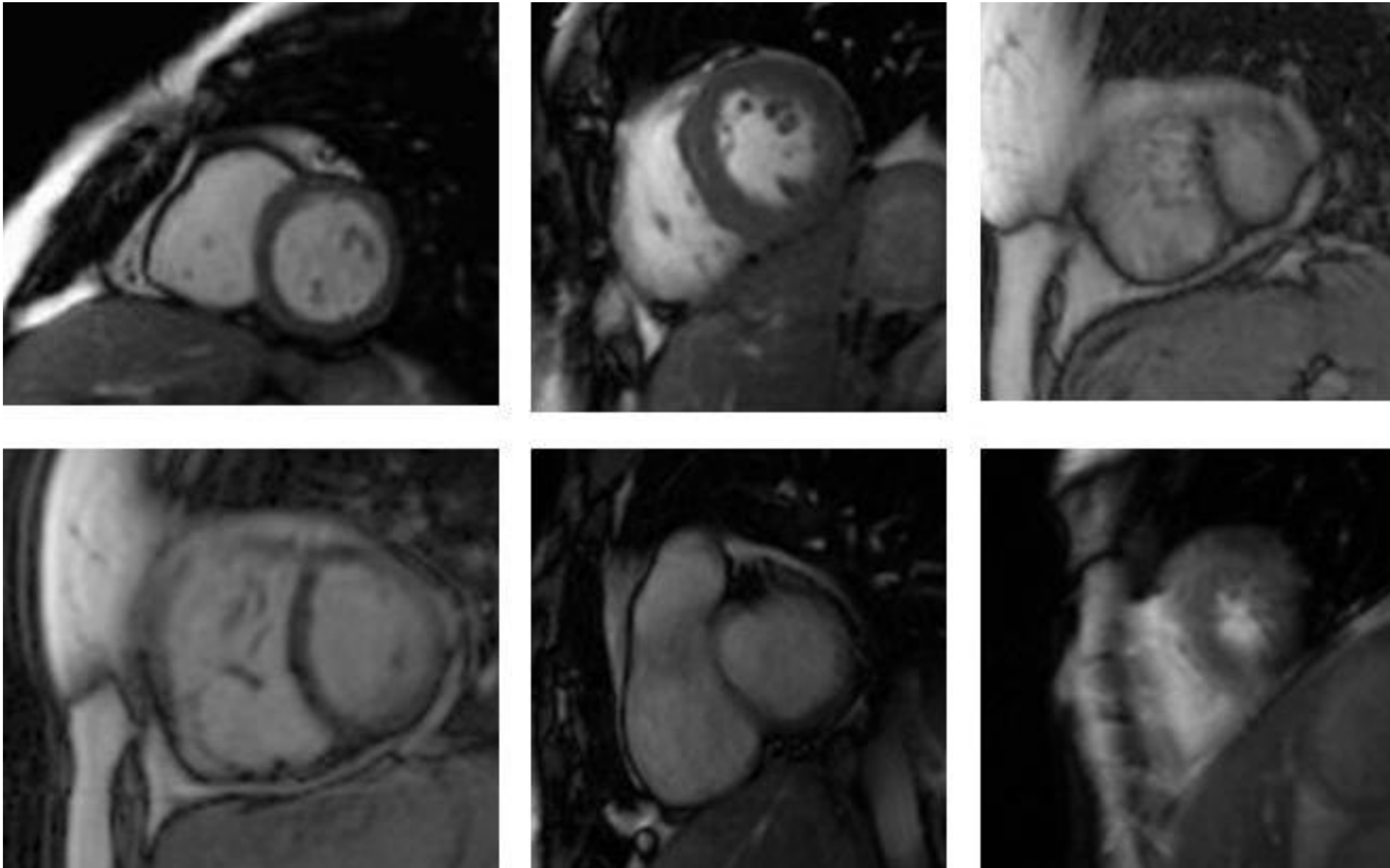


Foulonneau'04

Sans a priori

Avec a priori

Prior information based segmentation



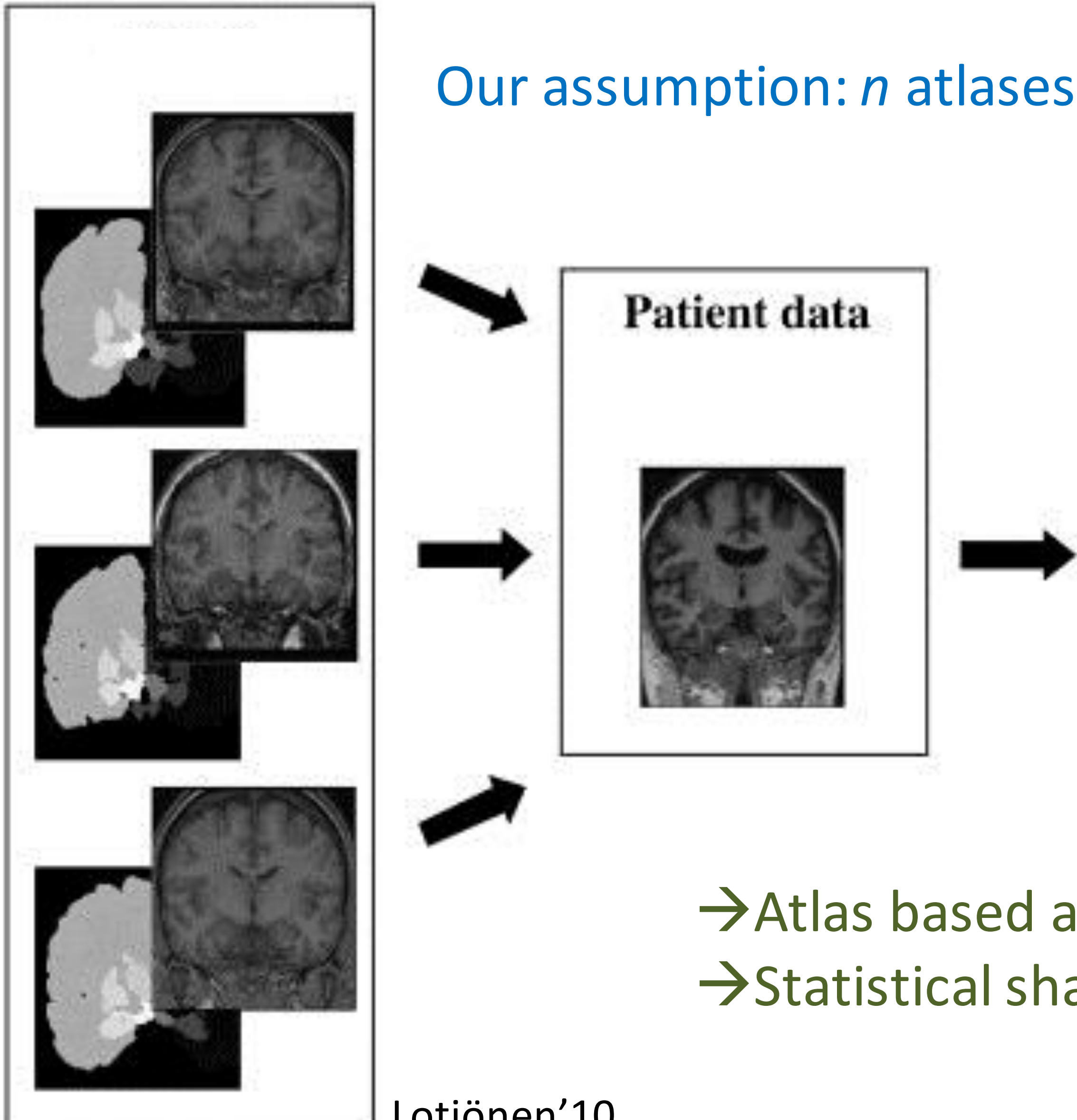
Prior information based segmentation

Foulonneau'04 Sans a priori Avec a priori

Etyngier'07

Prior information based segmentation

Our assumption: *n* atlases or label maps



Lotjönen’10

Segmentation of patient data ?

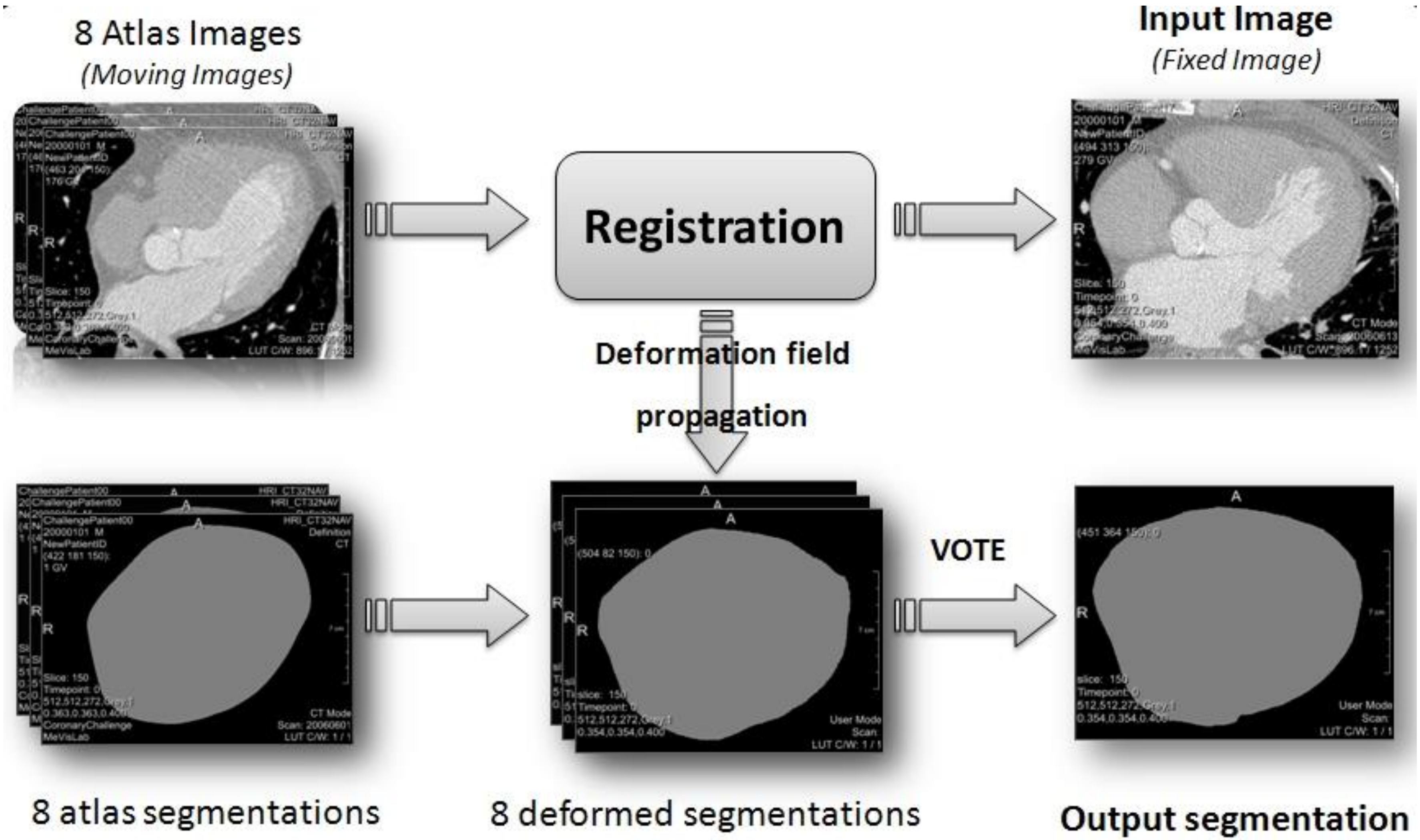
→Atlas based approaches

→Statistical shape prior based approaches

Outline

- Related works in prior information segmentation
  - Atlas based approaches
  - Statistical shape prior based approaches
- Manifold learning for shape set modelling
- ML-based shape prior segmentation framework
- A few results on cardiac MRI

Multi-atlas registration for image segmentation



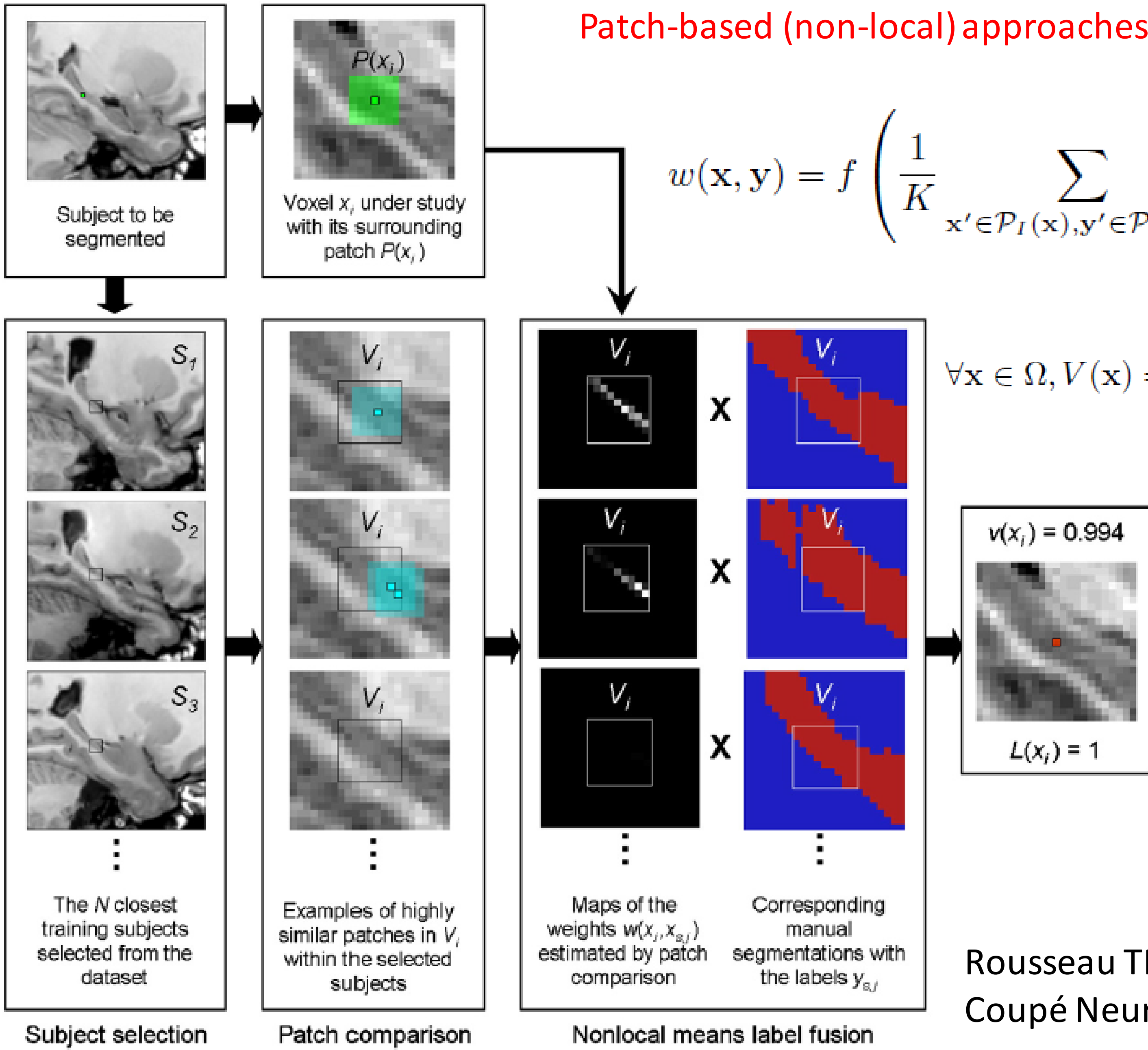
Kirisli'10

Multi-atlas: recent developments

Patch-based (non-local) approaches

$$w(\mathbf{x},\mathbf{y}) = f\left(\frac{1}{K}\sum_{\mathbf{x}'\in\mathcal{P}_I(\mathbf{x}),\mathbf{y}'\in\mathcal{P}_{\mathcal{I}_i}(\mathbf{y})}(I(\mathbf{x}')-\mathcal{I}_i(\mathbf{y}'))^2\right)$$

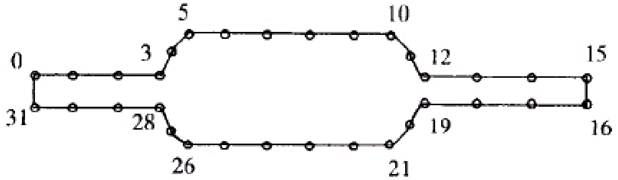
$$\forall \mathbf{x}\in\Omega, V(\mathbf{x}) = \frac{\sum_{\mathbf{y}\in\mathcal{N}(\mathbf{x})} w(\mathbf{x},\mathbf{y})\mathcal{L}(\mathbf{y})}{\sum_{\mathbf{y}\in\mathcal{N}(\mathbf{x})} w(\mathbf{x},\mathbf{y})}$$



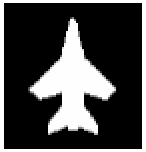
Rousseau TMI'10
Coupé NeuroImage'11

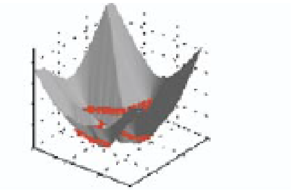
Statistical shape model for image segmentation

- **Objective:**
  - learn the possible shape deformations of an object statistically from a set of training shapes
  - restrict the contour deformation to the subspace of familiar shapes during the segmentation process
  - Active Shape Models, Cootes 1995



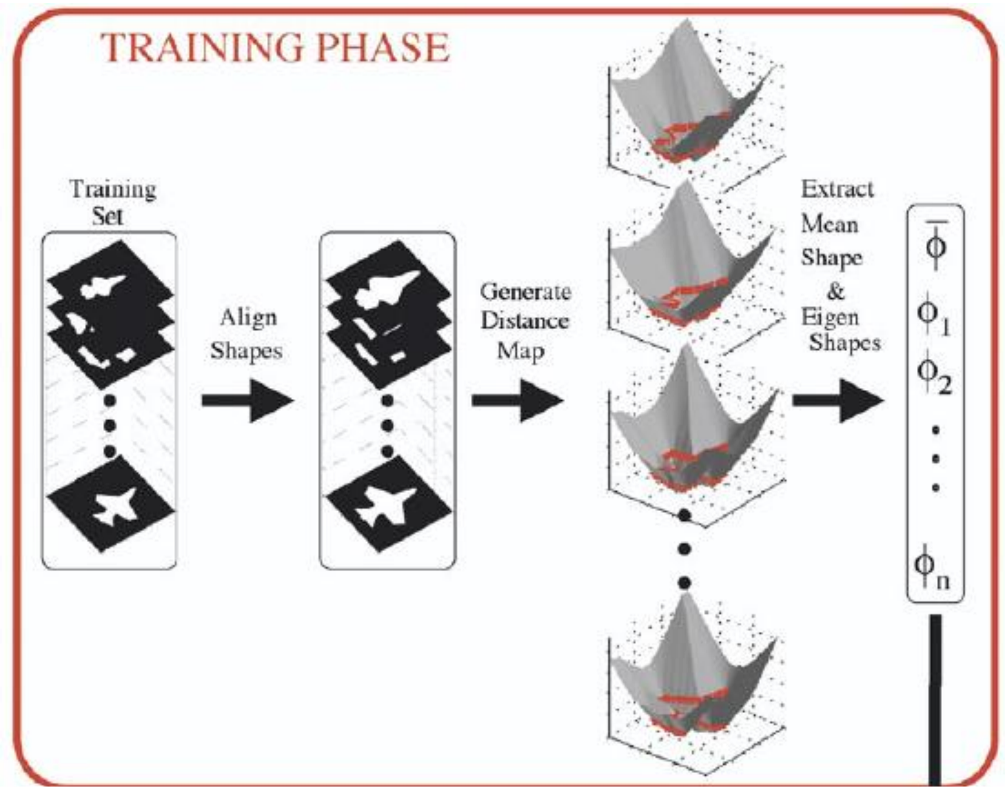
  - Leventon CVPR’00, Tsai TMI’03
    - Implicit representation





Statistical shape model for image segmentation

Example: Tsai's framework



Shapes are represented as signed distance functions

$$\mathbb{D}_\gamma = \varepsilon(x) \inf_{y \in \partial s} d(x,y) \text{ with } \varepsilon(x) \begin{cases} +1 & \text{if } x \in s, \\ -1 & \text{if } x \notin s \end{cases}$$

After rigid alignment:

$$\Phi[\mathbf{w},\mathbf{p}](x,y) = \bar{\Phi}(\tilde{x},\tilde{y}) + \sum_{i=1}^{k} w_i \Phi_i(\tilde{x},\tilde{y})$$

Mean shape

Eigenshapes

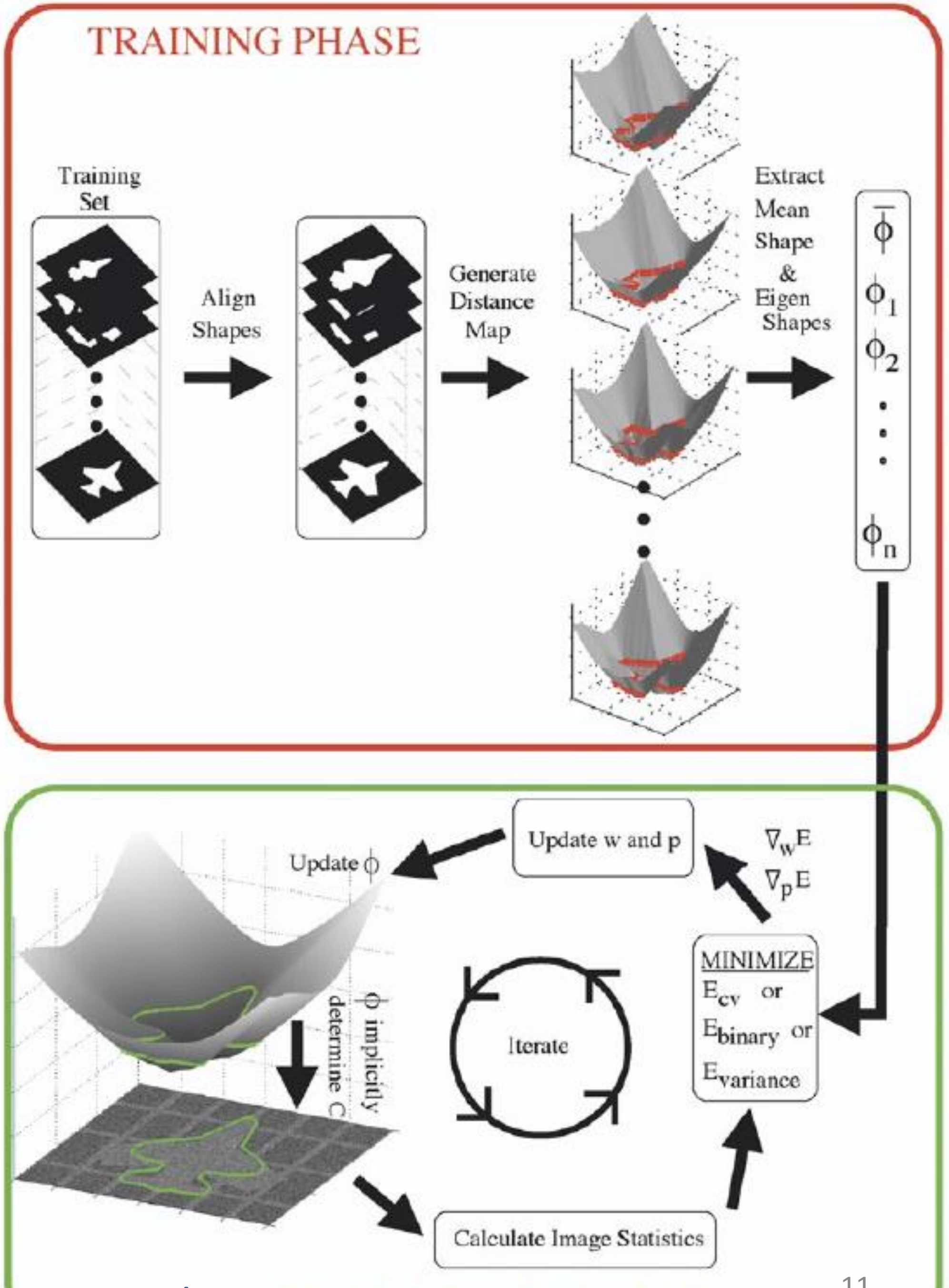
Statistical shape model for image segmentation

Example: Tsai's framework

$$\Phi[\mathbf{w},\mathbf{p}](x,y) = \bar{\Phi}(\tilde{x},\tilde{y}) + \sum_{i=1}^{k} w_i \Phi_i(\tilde{x},\tilde{y})$$

$$E_{\text{cv}} = \int_{R^u} (I-\mu)^2 dA + \int_{R^v} (I-\nu)^2 dA$$

$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \alpha_{\mathbf{w}} \nabla \mathbf{w} E$$
$$\mathbf{p}^{(t+1)} = \mathbf{p}^{(t)} - \alpha_{\mathbf{p}} \nabla \mathbf{p} E$$



Tsai TMI'03

Problems of linear shape space

- Assumes the data lie in a linear subspace
- permissible shapes are assumed to form a multivariate Gaussian distribution

Yet: real world data sets present complex deformations

- Non linear shape statistics for image segmentation
  - introduced with kPCA in Cremers, ECCV'02
  - with manifold learning techniques: Etyngier'07, Yan'13, Moolan-Ferouze'14…

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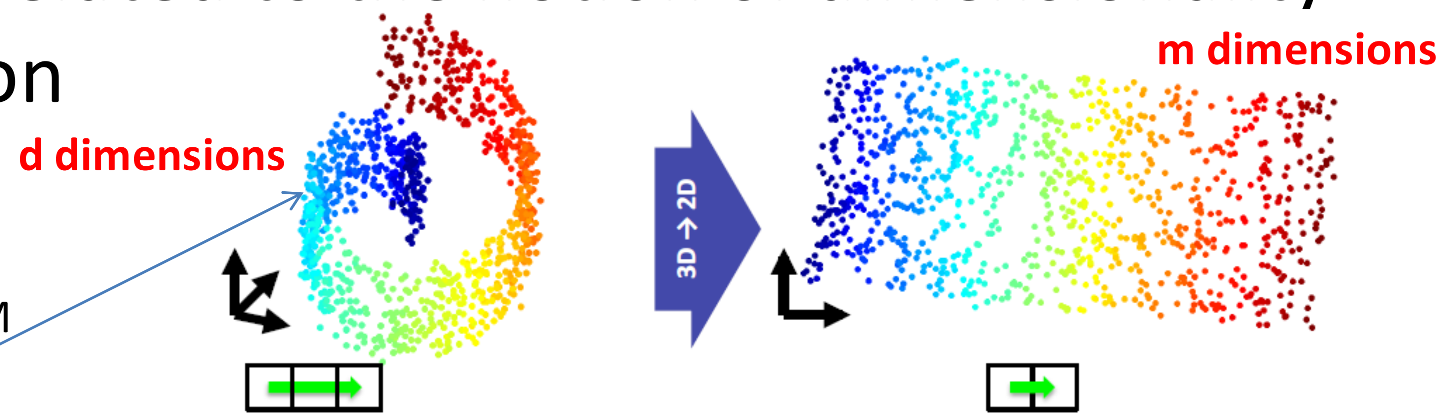
Manifold learning

- process of recovering the <u>underlying low dimensional structure</u> of a manifold that is embedded in a higher-dimensional space

- closely related to the notion of dimensionality reduction

Each shape SDM is vectorized

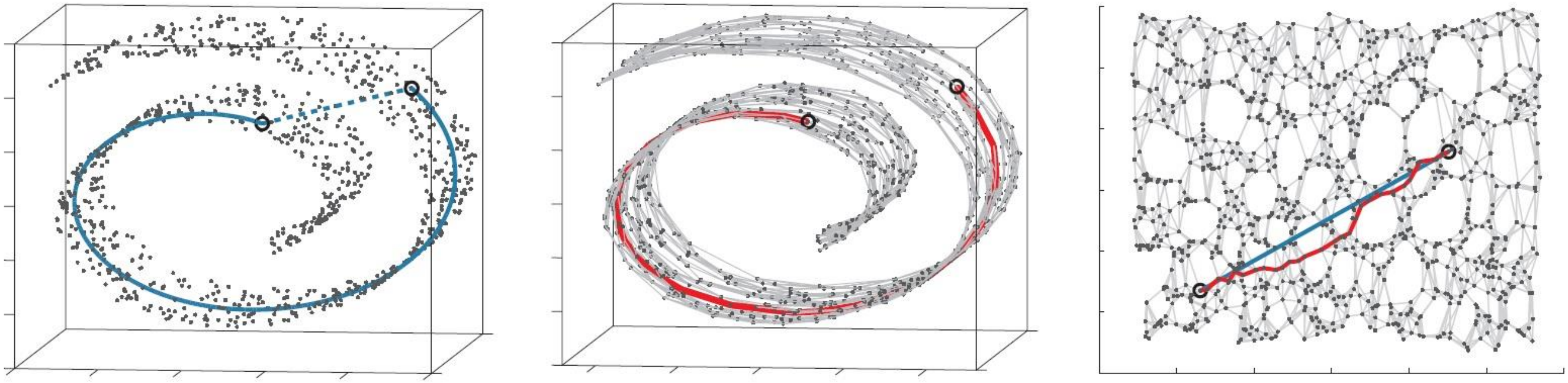


$\Xi = [\xi_i]_{1 \leq i \leq N}$ $\quad$ $\mathbf{X} = [\mathbf{x}_i]_{1 \leq i \leq N}$

Source: J. Lee, UCLouvain, nov'14 seminar

Principle of spectral ML techniques

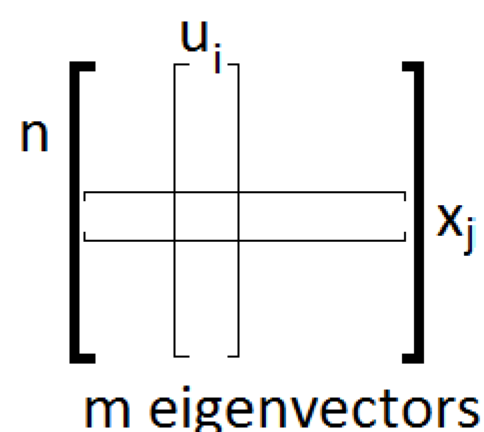
- Compute a similarity matrix M (*n x n*) between *n* points (= shapes for us) of the dataset
  - Goal: to connect points that lie within a common neighbourhood.
    - *k-nearest neighbour or ϵ - ball*



http://isomap.stanford.edu/

Principle of spectral ML techniques

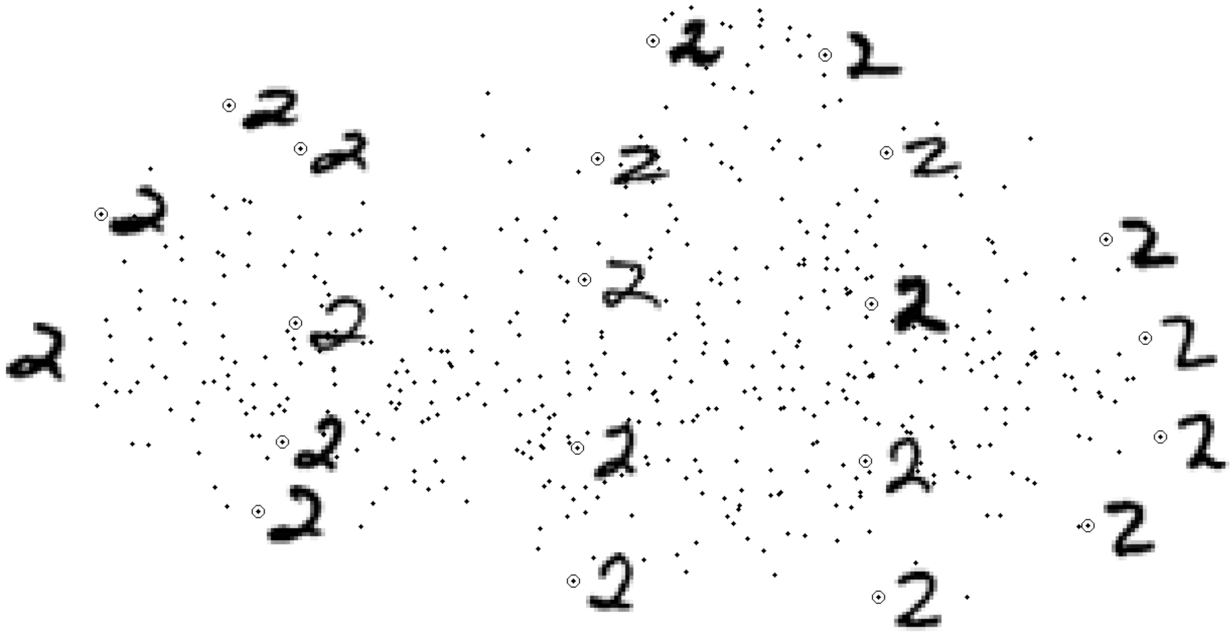
- Compute a similarity (affinity) matrix M (*n x n*)
- From M, compute a feature matrix F:
  - size n x n
  - symmetric
  - positive semi definite
- Spectral decomposition of F
- Keep the m smallest/largest eigenvectors

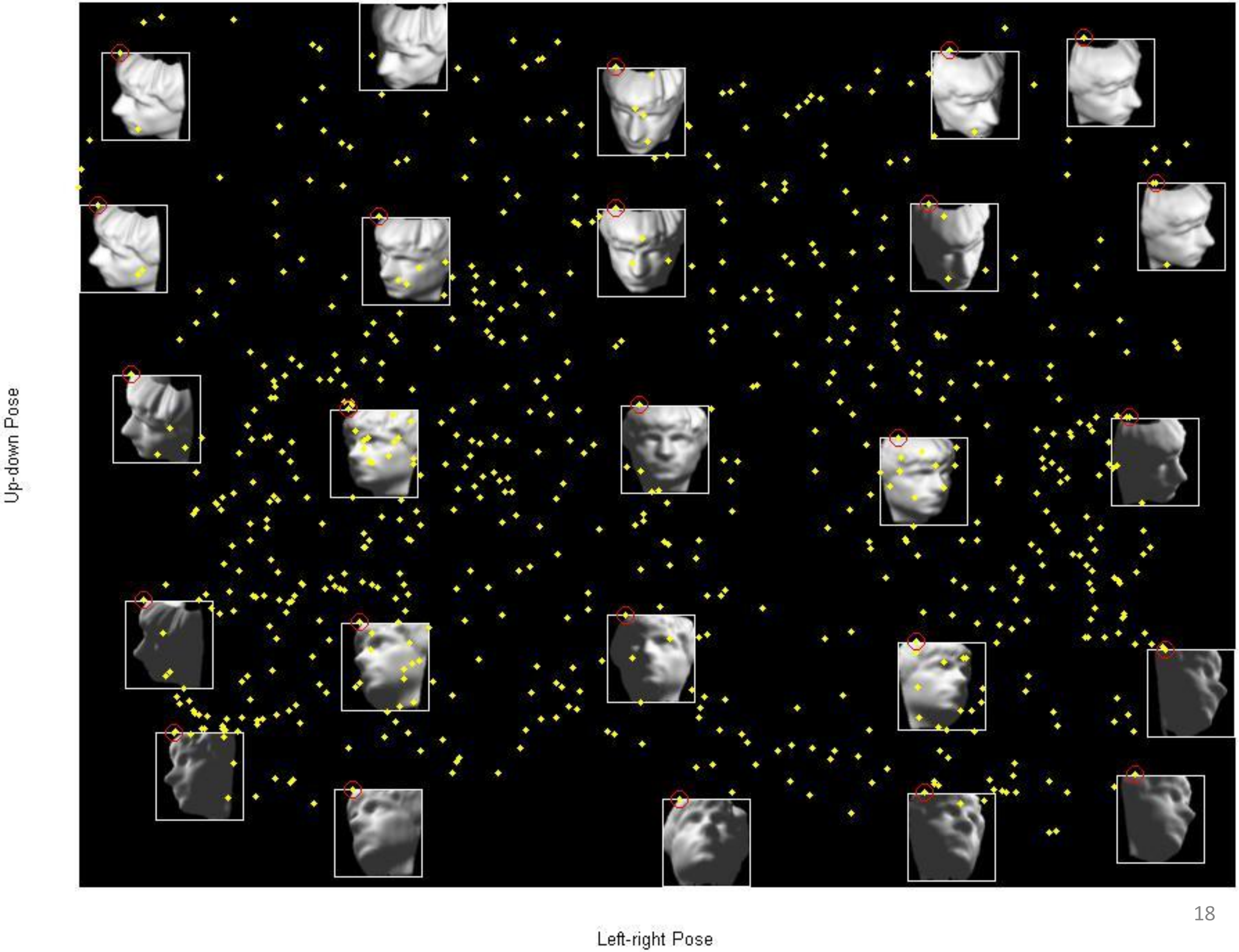


Cf Shi & Malik's Normalized cuts (PAMI'00)

An example

- Number two in MNIST database (n=500)
  - Images: 20 x 20 
  - d = 400 → m = 2





Up-down Pose
Left-right Pose

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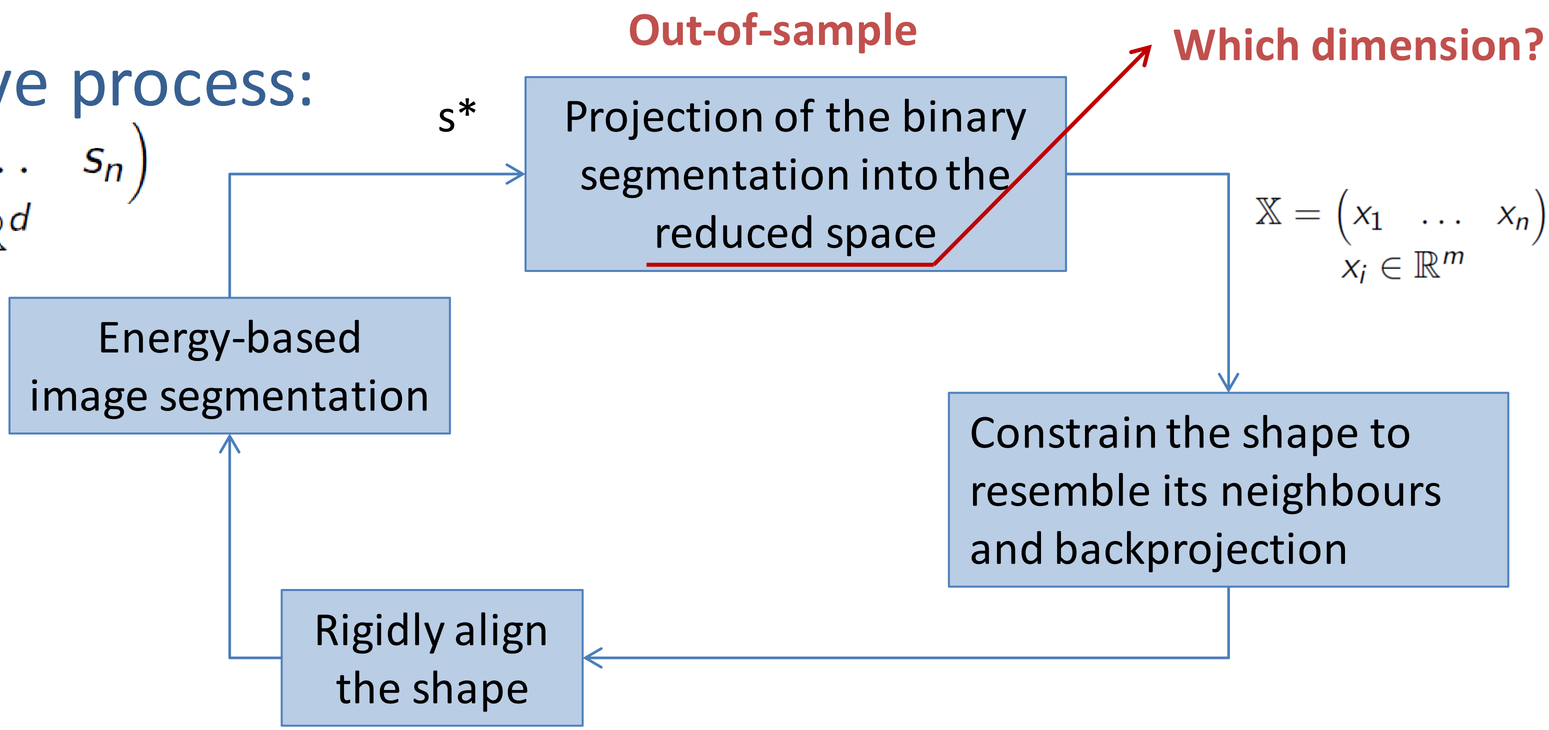
How to use an non linear shape prior for segmentation?

- Iterative process:

$$\mathbb{S} = \begin{pmatrix} s_1 & \dots & s_n \end{pmatrix}$$
$$s_i \in \mathbb{R}^d$$



Based on Etyngier ICCV'07 &
Moolan-Ferouze MICCAI'14

How to use an non linear shape prior for segmentation?

x*: shape of the segmentation result in the reduced space

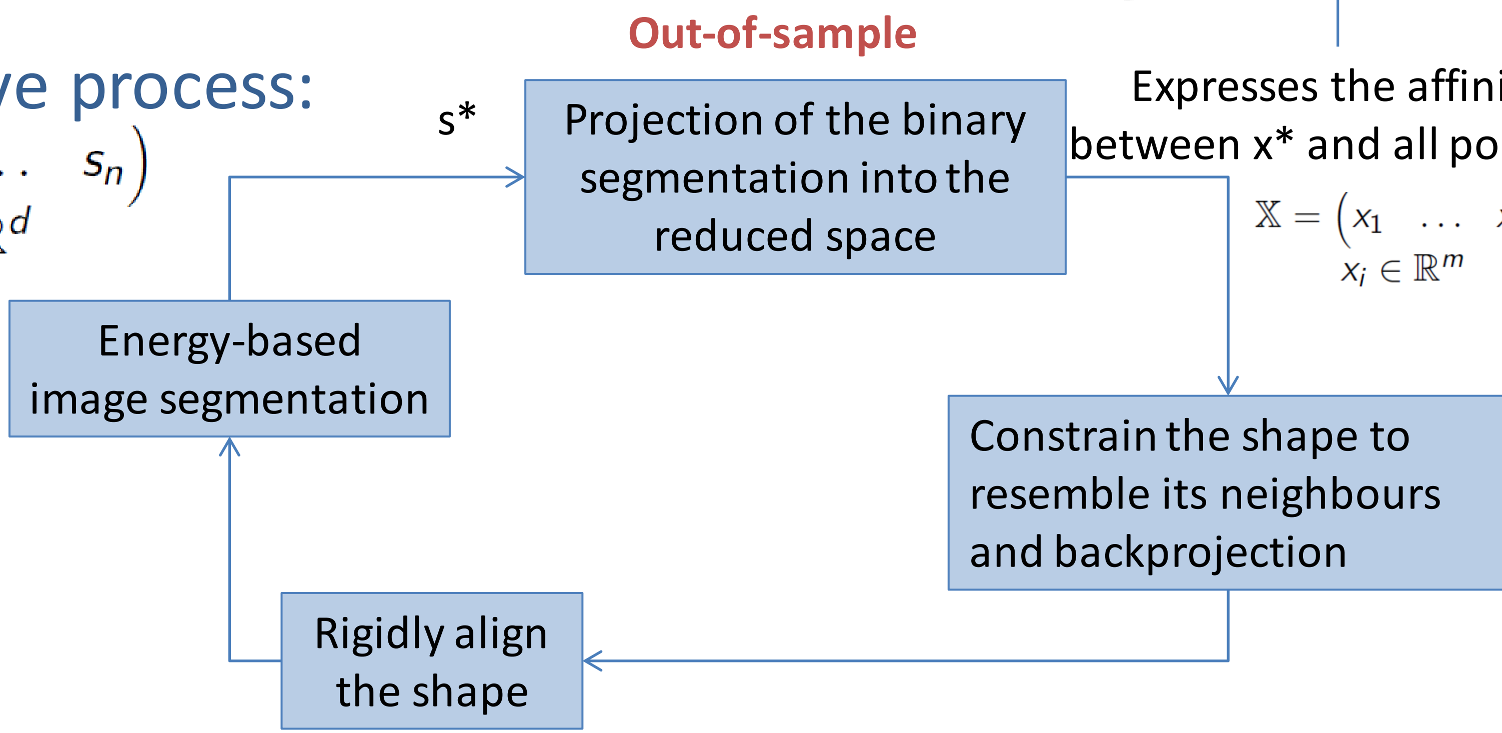
$$\mathbf{x}^* = \frac{1}{\lambda_k} \sum_{j=1}^{n} \mathbf{u}_{kj} K(\mathbf{x}^*, \mathbf{x}_j)$$

Expresses the affinity between x* and all points x_j

$$\mathbb{X} = \begin{pmatrix} x_1 & \dots & x_n \end{pmatrix} \quad x_i \in \mathbb{R}^m$$

- Iterative process:

$$\mathbb{S} = \begin{pmatrix} s_1 & \dots & s_n \end{pmatrix} \quad s_i \in \mathbb{R}^d$$



Based on Etyngier ICCV'07 & Moolan-Ferouze MICCAI'14

Constrain the shape in the embedding

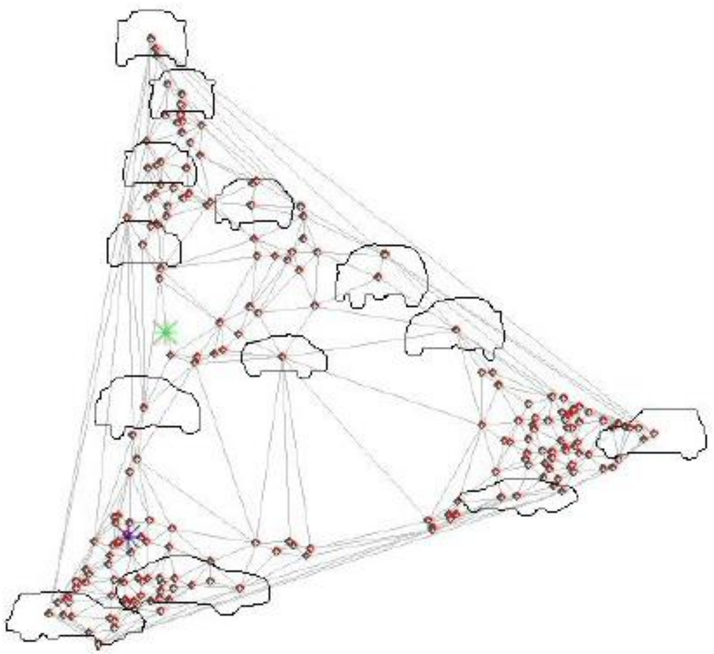
Moolan-Ferouze '14

- Find the shape's nearest neighbors (NN)
- The shape $\hat{s}$ is a linear combination of its NN:

$$\hat{s} = \sum_{i=0}^{m} \theta_i s_i \quad \text{with } \sum_{i=0}^{m} \theta_i = 1 \text{ and } \theta_i \geq 0, \forall i = 0, \ldots, m$$

$$\hat{\theta} = \arg\min d\,(s^*, \hat{s})$$

$$with \quad d\,(s^*, \hat{s}) = \sum (H(s^*) - H(\hat{s}))^2$$



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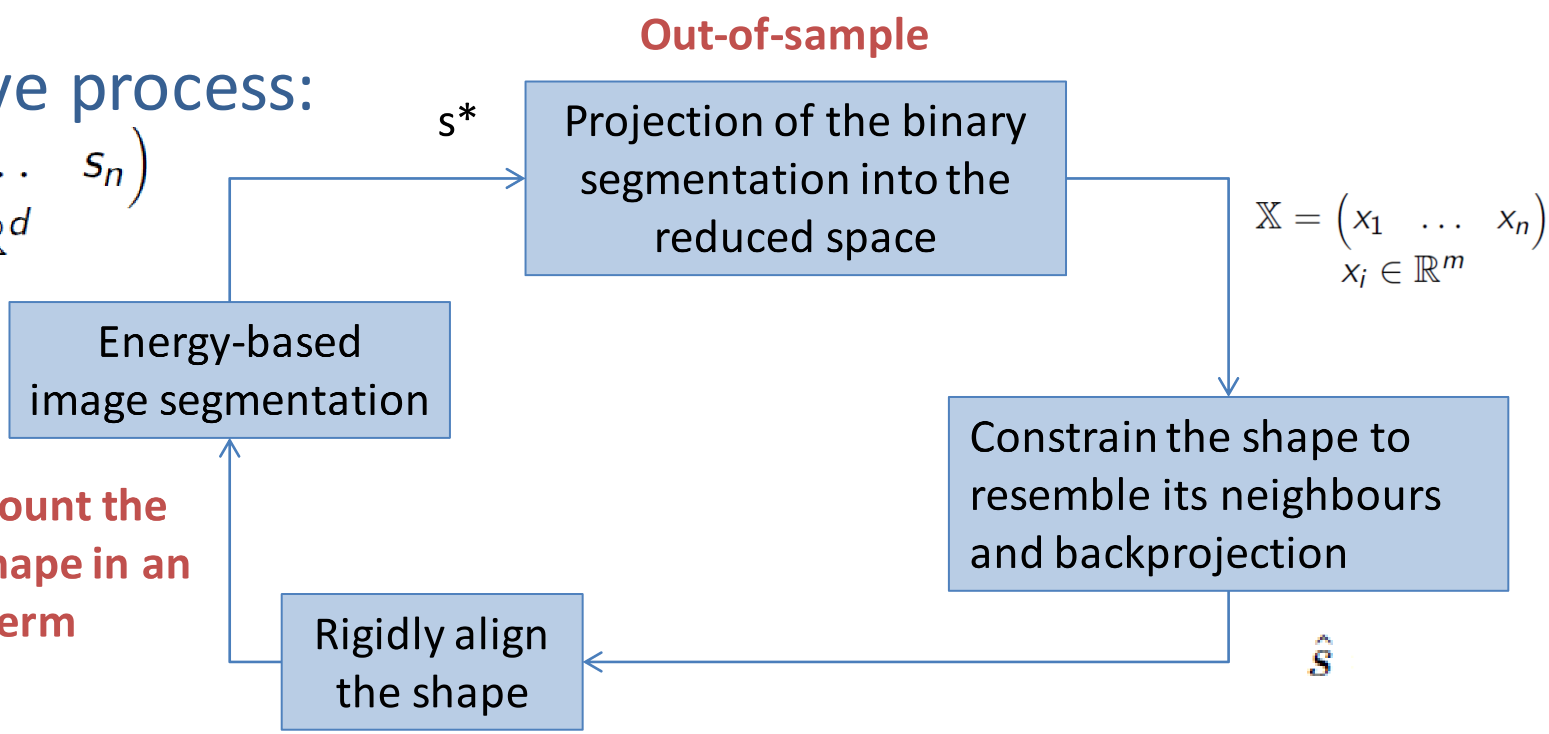

Take into account the constrained shape in an energy term

Based on Etyngier ICCV’07 & Moolan-Ferouze MICCAI’14

How to use an non linear shape prior for segmentation?

- Iterative process:

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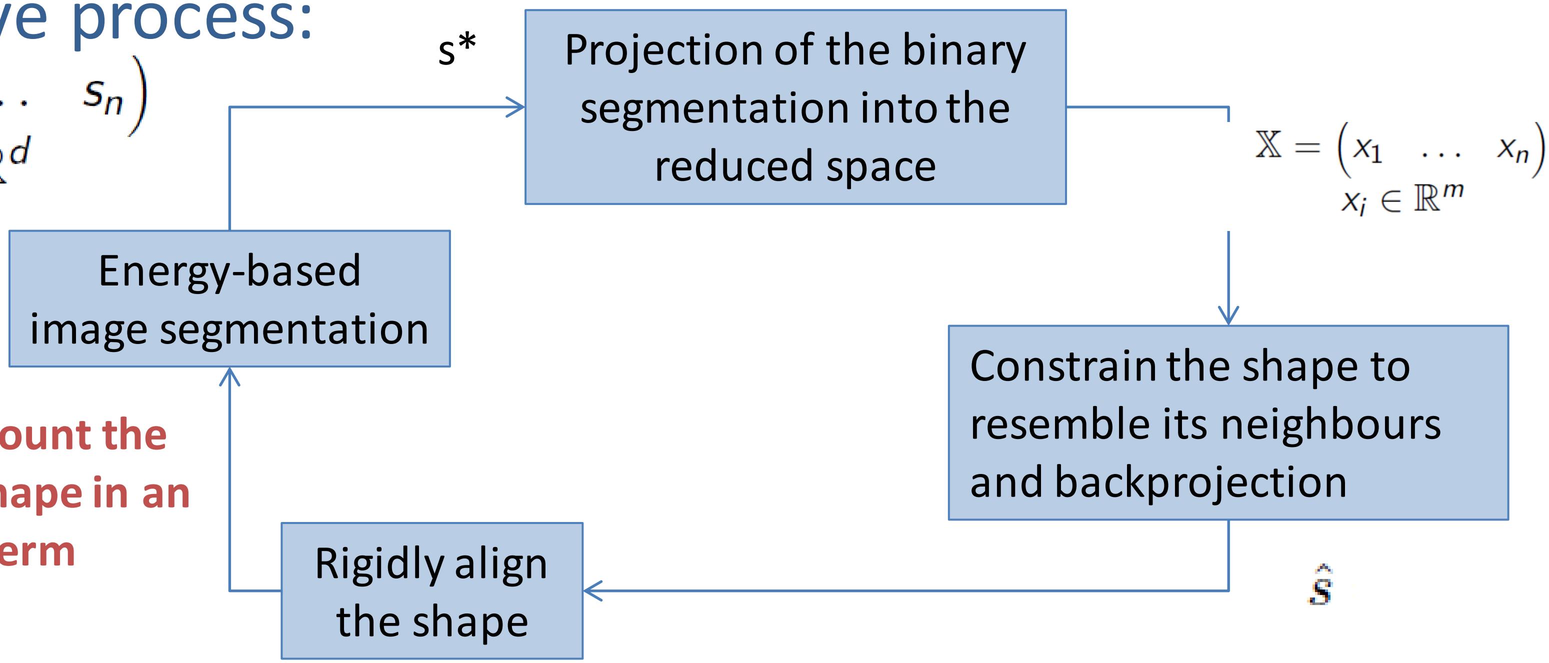


Take into account the constrained shape in an energy term

$$E_{total}(L) = E_{data}(L) + E_{smooth}(L) + E_{prior}(L)$$

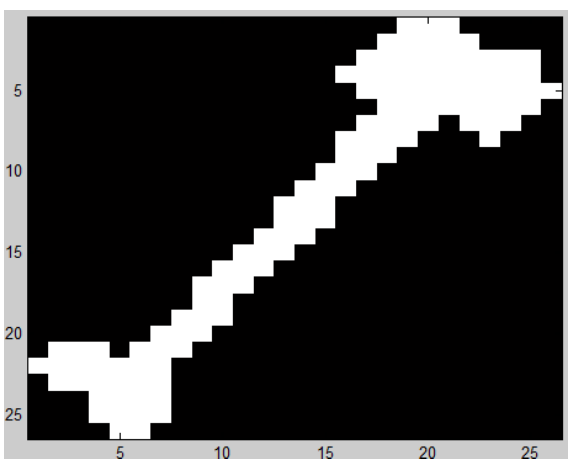
Find the labeling L such that E(L) is minimum

Shape prior energy term

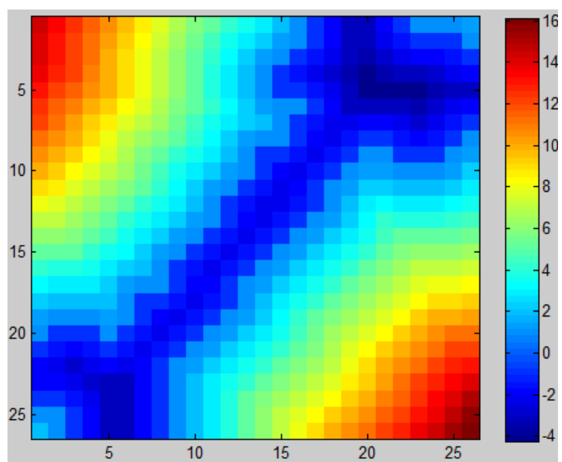
Find the labeling L such that E(L) is minimum

$E_{prior}(O)$
$E_{prior}(B)$
designed to be small for pixels likely to be labelled as
object
background

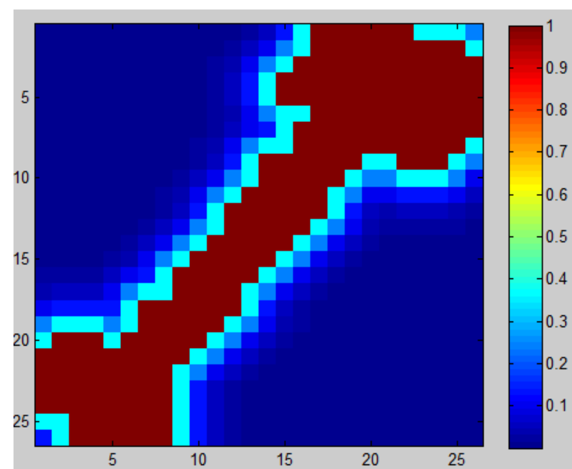
From $\hat{s}$, let's define a probability atlas



Binary shape



Signed distance map



$$M(i) = \begin{cases} 1 & \text{if} \quad \hat{s}(i) \leq 0 \\ e^{-\hat{s}(i)/\gamma_{f(i)}} & \text{if} \quad \hat{s}(i) > 0 \end{cases}$$

Shape prior energy term

Find the labeling L such that E(L) is minimum

$E_{prior}(O)$
$E_{prior}(B)$
designed to be small for pixels likely to be labelled as
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background

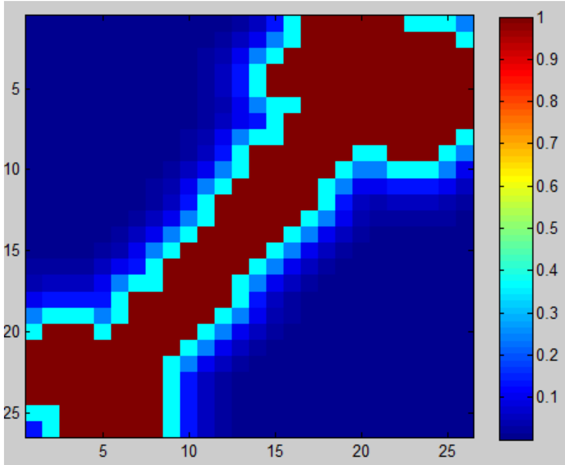
From $\hat{s}$, let's define a probability atlas

Shape prior term:

$$E_{prior}(O) = -\sum_i \log(M(i))$$

$$E_{prior}(B) = -\sum_i \log(1 - M(i))$$

Moolan-Ferouze MICCAI'14

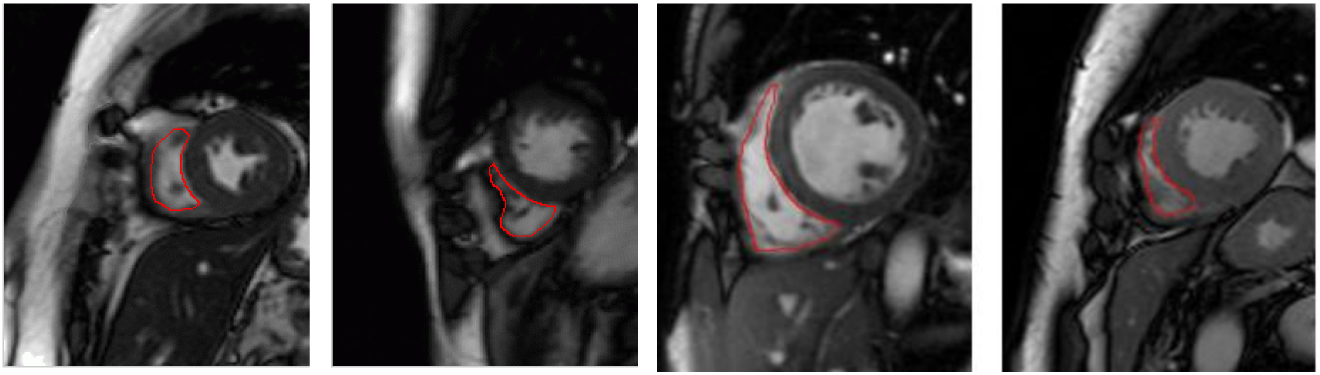


$$M(i) = \begin{cases} 1 & \text{if} \quad \hat{s}(i) \leq 0 \\ e^{-\hat{s}(i)/\gamma_{f(i)}} & \text{if} \quad \hat{s}(i) > 0 \end{cases}$$

E_{total} is minimized with the mincut – maxflow algorithm [Boykov+Kolmogorov'04]

Experimental results

- Application: segmentation of the right ventricle in cardiac MRI



- Implementation:

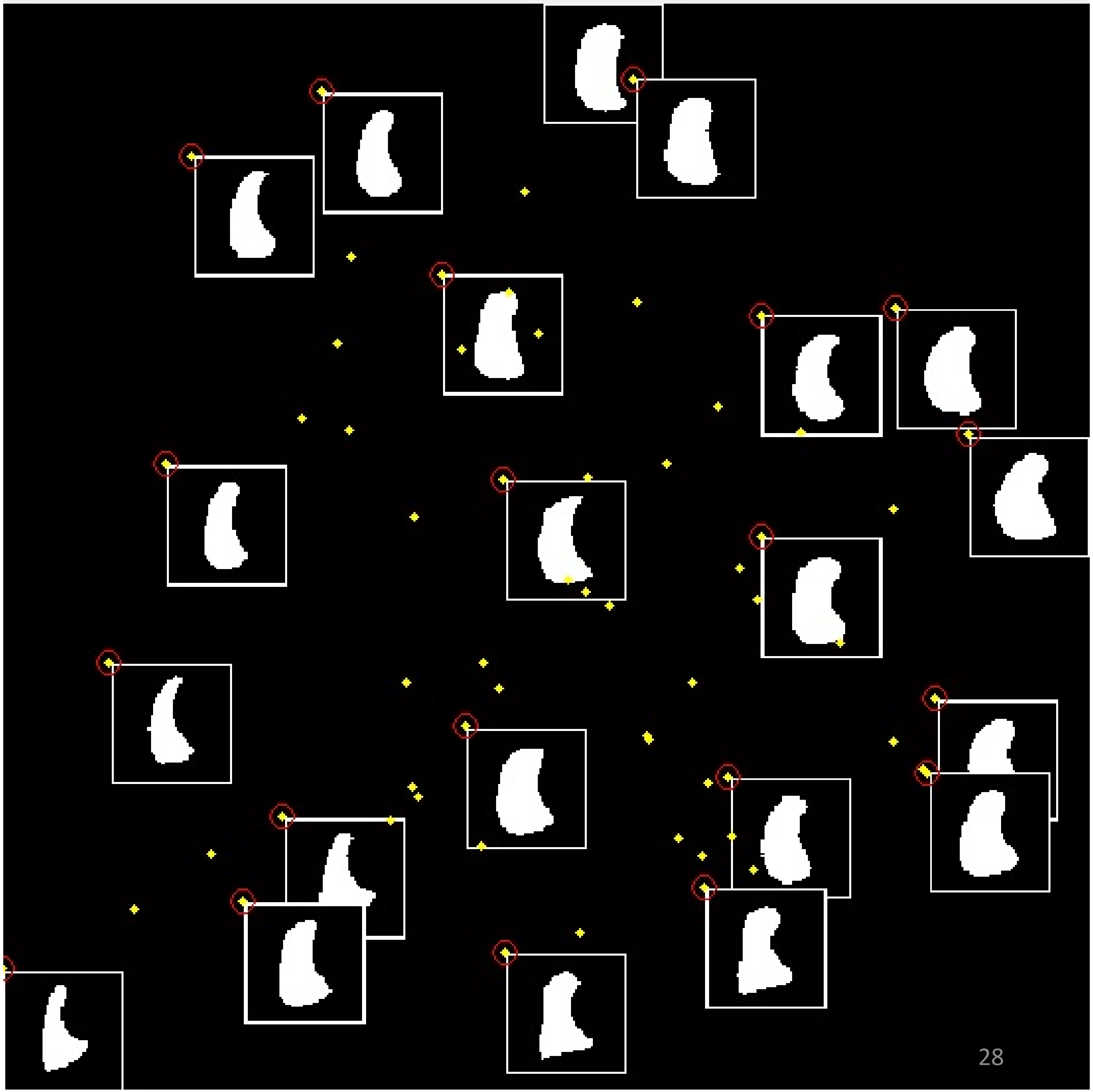
(travail réalisé avec Arturo Mendoza Quispe, étudiant M2 STIM)

  – Manifold learning: diffusion maps (Etyngier'07)
  – Graphcut based image segmentation
  – Shapes are described with signed distance maps

Experimental results

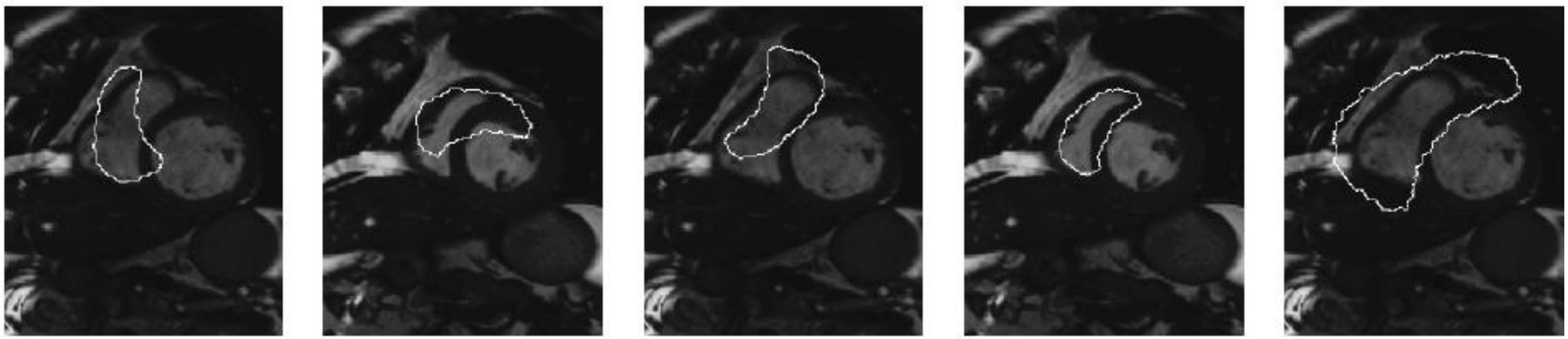
RV shape
in 2D space

(intrinsic dim≈3)

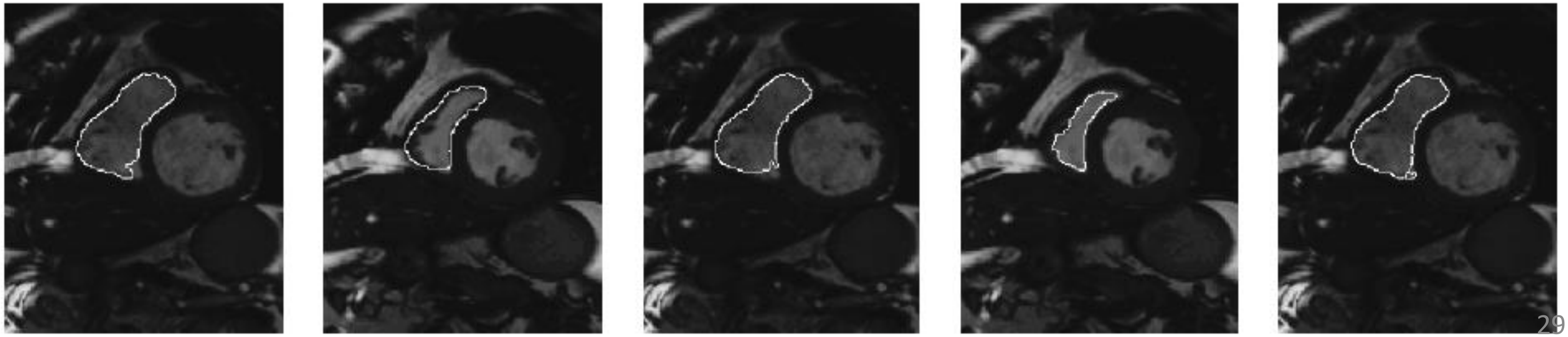


Experimental results

Initializations

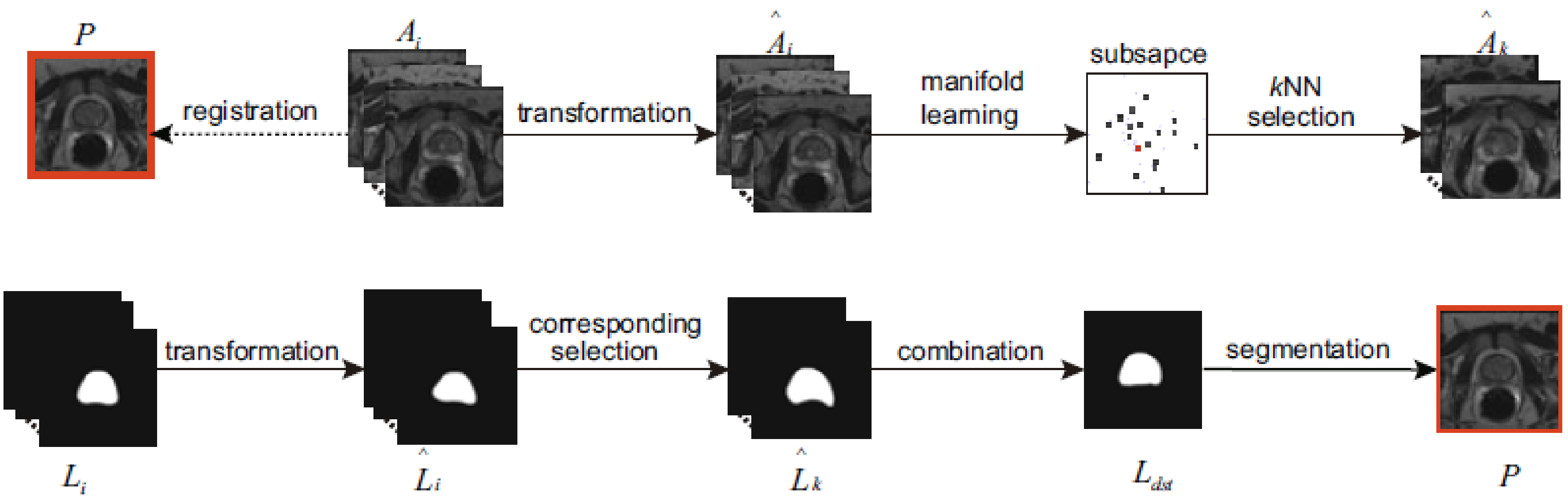


Final segmentations



Some perspectives with ML techniques

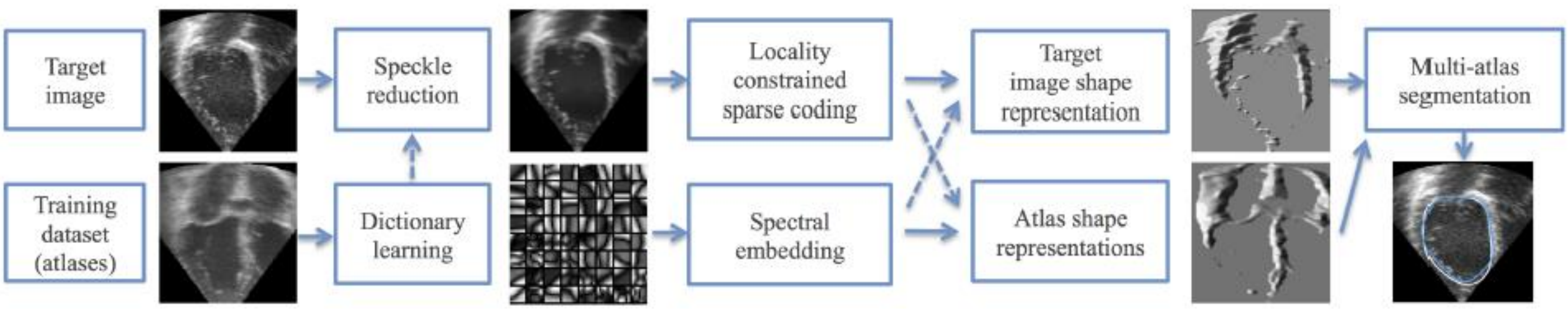
- Also investigated for atlas-based approaches
  - ML for atlas selection [Wolz NeuroImage'10, Cao MICCAI'11, Hoang-Duc PlosOne'13, Gao SPIE'14]



Cao MICCAI'11

Some perspectives with ML techniques

- Also investigated for atlas-based approaches
  - ML for atlas selection [Wolz NeuroImage'10, Cao MICCAI'11, Hoang-Duc PlosOne'13, Gao SPIE'14]
  - Patch-based approaches [Shi et al MICCAI'14, Oktay et al MICCAI'14]
    – Sparse representation and dictionary learning



Oktay et al MICCAI'14

Merci !

- … pour votre attention.
- Commentaires ? Questions ?

- Caroline.Petitjean@univ-rouen.fr