Image Segmentation based on Deformable Models

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ASCLEPIOS Team

INRIA Sophia-Antipolis

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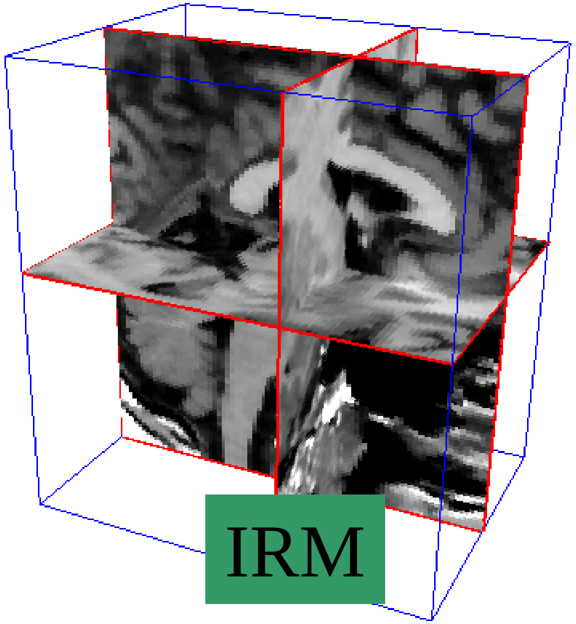
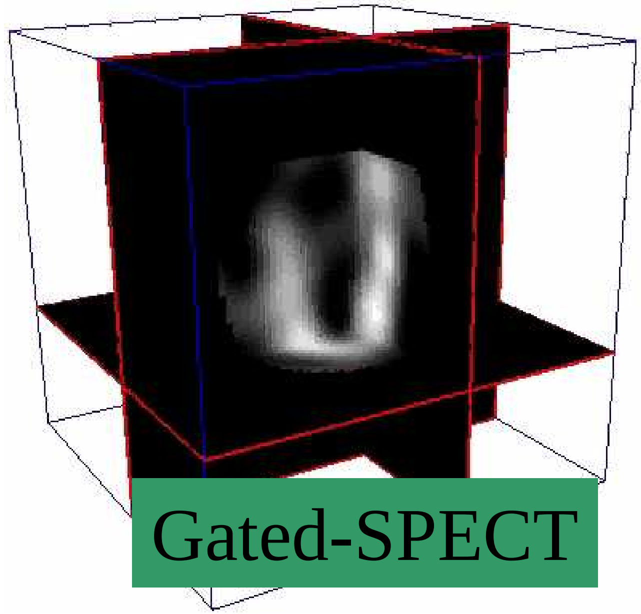
Segmentation d’Images

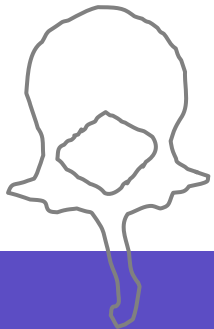


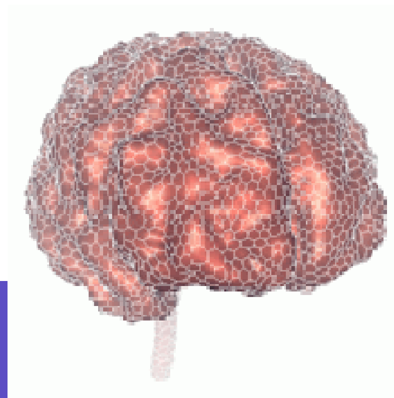


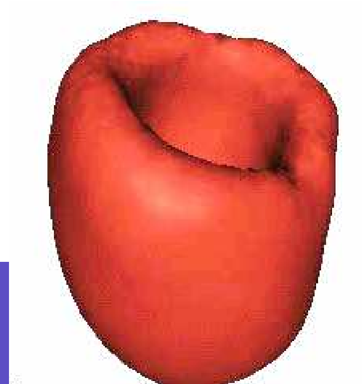
2D

3D

4D (3D+T)







Approches Basées Voxels

Images Médicales

↓

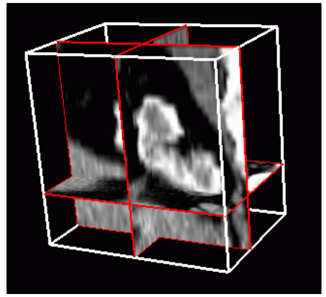
Extraction d'Amers

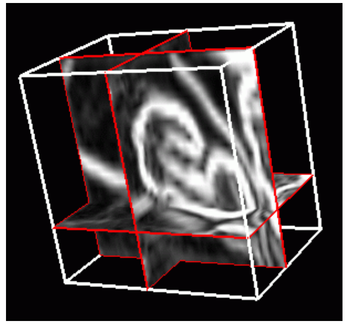
↓

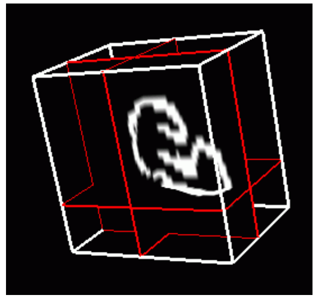
Groupement d 'Amers

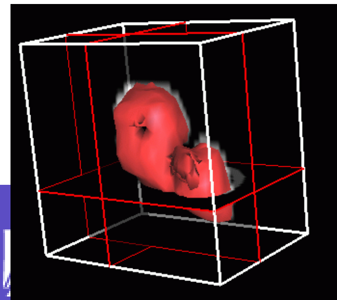
↓

Région/Frontière Extraction









Approches Basées Modèles

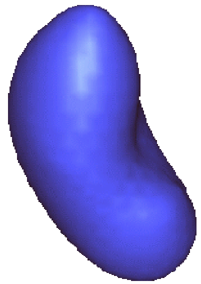
Construction de Modèles: Forme et Apparence

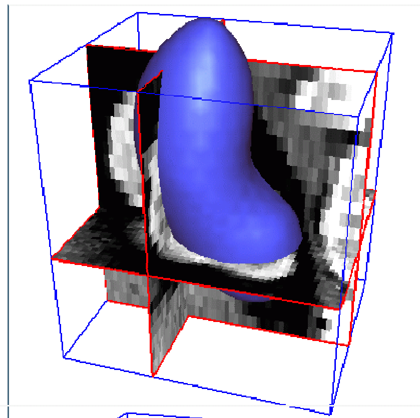
↓

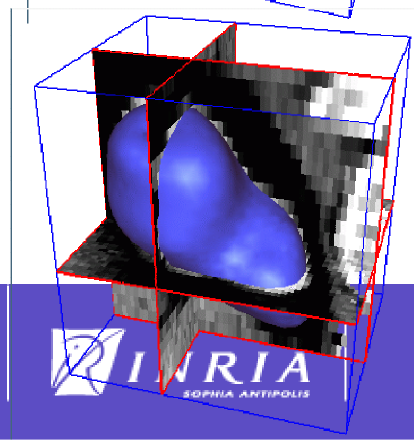
Initialisation du Modèle

↓

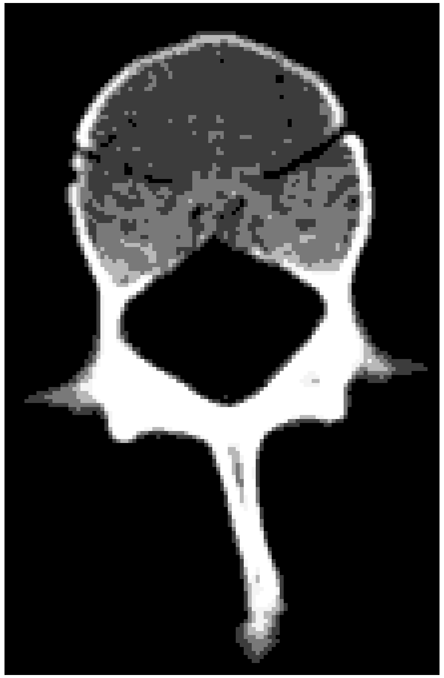
Ajustement du Modèle



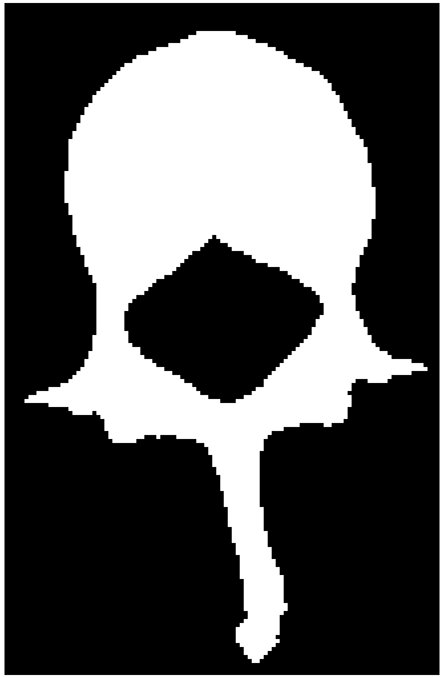




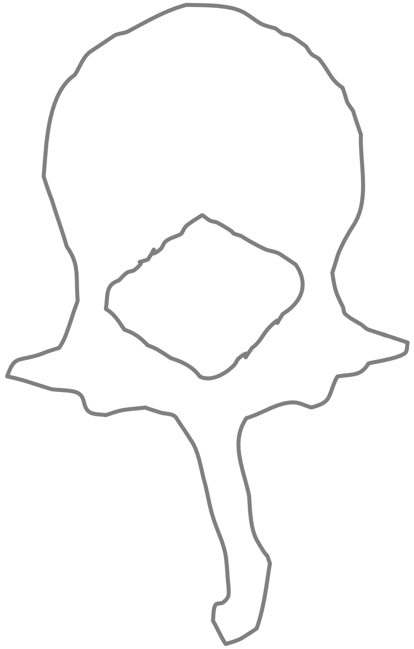
Méthodes Région ou Frontière



Image



Segmentation Région



Segmentation Frontière

Deux Méthodes de Segmentation

Description de 2 méthodes de segmentation :

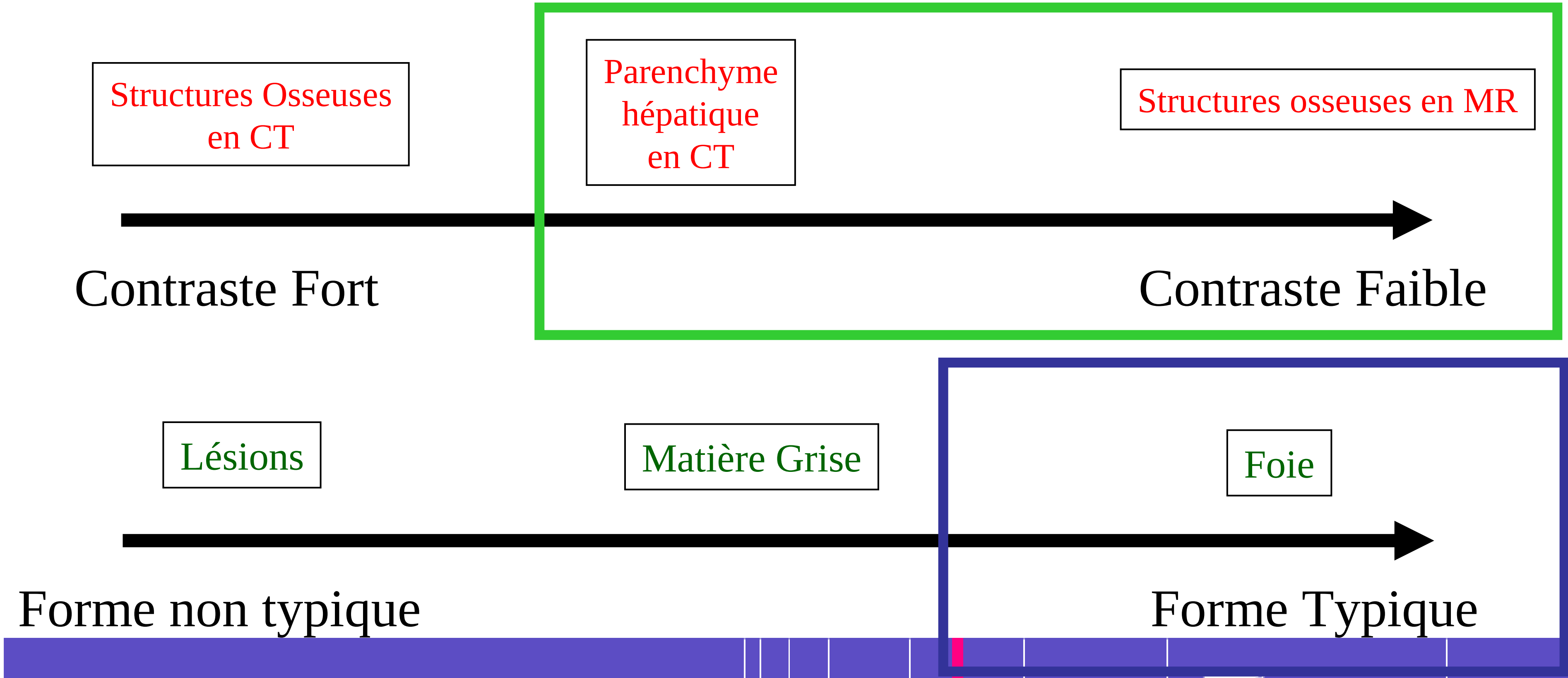
- **Basée Voxel** : Seuillage /Classification
- **Basée Modèle** :Modèles déformables 3D et 4D

	Thresholding /Classification	Deformable Models	Markov Random Field
Shape Information	None	Important	local
Intensity Information	Essential	Important	Important
Boundary / Region	Region	Boundary	Region

Pas d'algorithme universel de segmentation

Un algorithme donné a un domaine d'application limité

Exemple : Modèles déformables



Principe de la segmentation par modèle déformable

Définition de l'énergie :

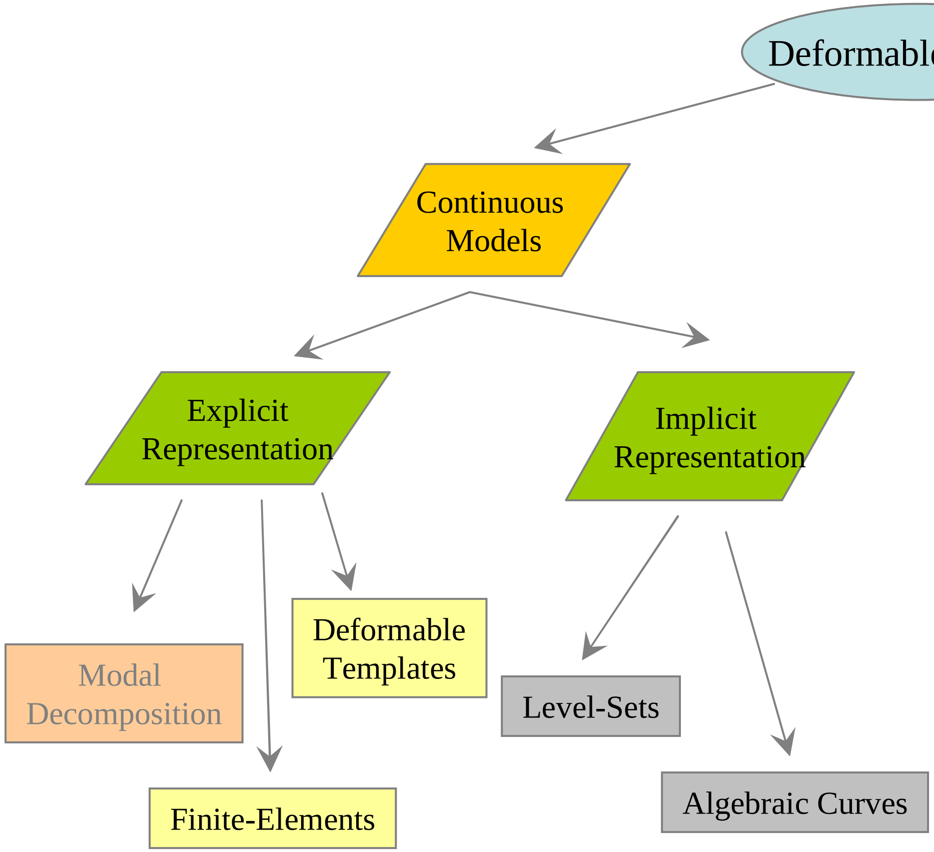
$$E = E_{\text{int}} + E_{\text{ext}}$$

E_{int} mesure la régularité de la courbe/surface

E_{ext} mesure la distance du contour/surface à la frontière de l'objet à contourer

Position du problème : minimiser E

Surface Representation for Deformable models



Why Choose Simplex Mesh ?

Against parametric surfaces

- 🙂 It does not require any global parameterization of the surface
- ☹ … but does not provide interpolation of differential parameters

Against triangulation

- 🙂 Easy method to control the spread of vertices (with metric parameters)
- 🙂 Can easily implement shape memory regularisation
- 🙂 Can smooth without any shrinkage
- ☹ … but no planar faces for visualisation

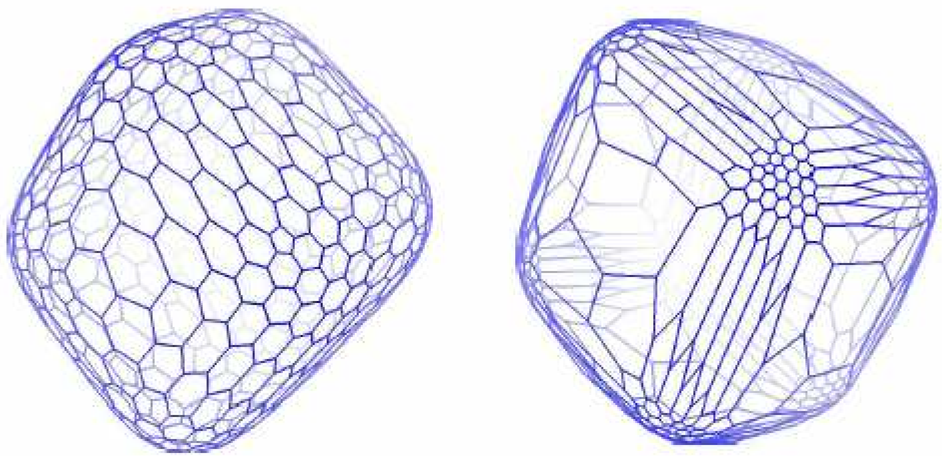
Against level-sets

- 🙂 Handle surfaces with borders
- 🙂 Store a-priori information at vertices, faces, zones
- 🙂 Regularization with global constraint and no shrinkage
- ☹ … but difficult to handle change of topology (self intersections) and highly curved surfaces

Regularization of simplex meshes

$$\sigma(\mathbf{P}_i) = (\epsilon^\star_{1i} - \epsilon_{1i})\mathbf{P}_{N_1(i)} + (\epsilon^\star_{2i} - \epsilon_{2i})\mathbf{P}_{N_2(i)} + (\epsilon^\star_{3i} - \epsilon_{3i})\mathbf{P}_{N_3(i)} +$$
$$(L(r_i, \phi^\star_i, \epsilon^\star_{1i}, \epsilon^\star_{2i}, \epsilon^\star_{3i}) - L(r_i, \phi_i, \epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i}))\,\mathbf{n}_i$$

Choice of ε_i^* controls vertex spacing



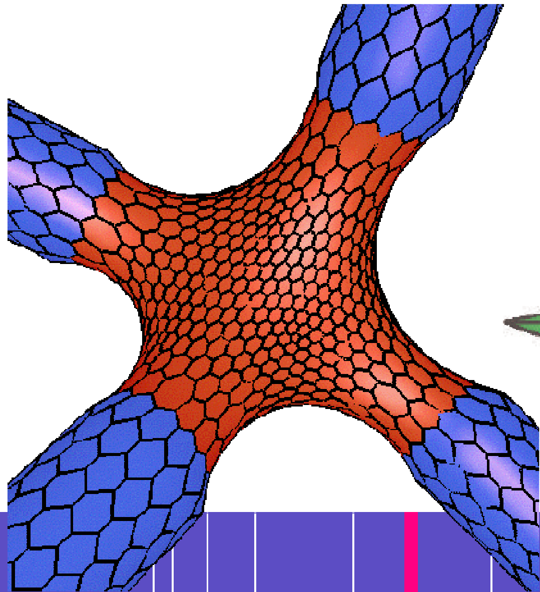
Regularization of simplex meshes

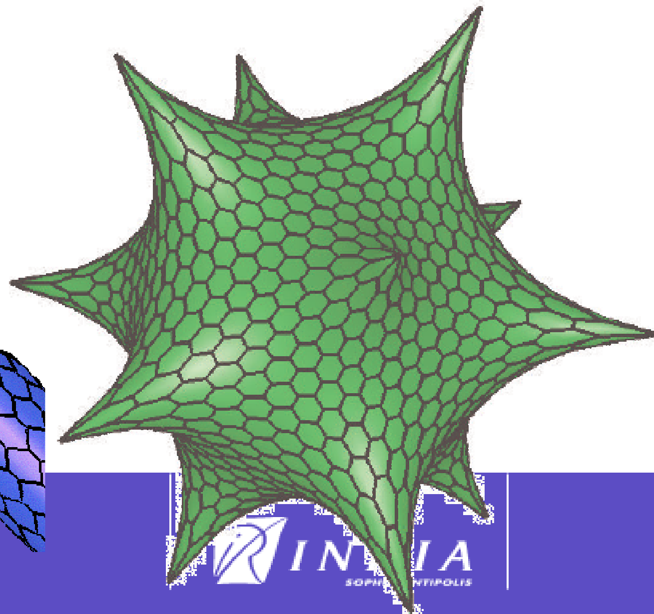
$$\sigma(\mathbf{P}_i) = (\epsilon^\star_{1i} - \epsilon_{1i})\mathbf{P}_{N_1(i)} + (\epsilon^\star_{2i} - \epsilon_{2i})\mathbf{P}_{N_2(i)} + (\epsilon^\star_{3i} - \epsilon_{3i})\mathbf{P}_{N_3(i)} +$$
$$\left(L(r_i, \phi^\star_i, \epsilon^\star_{1i}, \epsilon^\star_{2i}, \epsilon^\star_{3i}) - L(r_i, \phi_i, \epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i})\right)\mathbf{n}_i$$

Choice of ϕ_i* controls shape

C1 : Orientation continuity constraint

$$\phi_i^* = 0$$





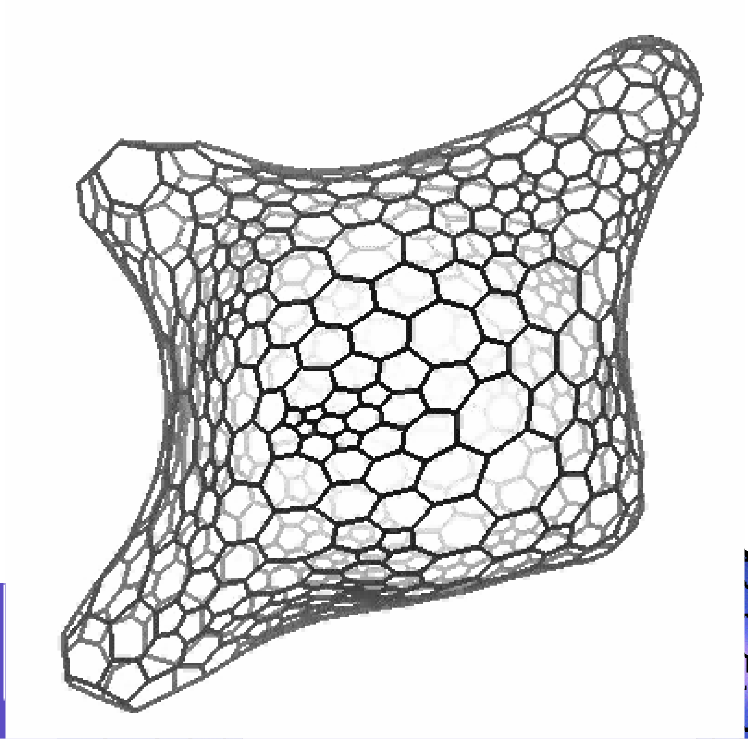
Regularization of simplex meshes

$$\sigma(\mathbf{P}_i) = (\epsilon_{1i}^\star - \epsilon_{1i})\mathbf{P}_{N_1(i)} + (\epsilon_{2i}^\star - \epsilon_{2i})\mathbf{P}_{N_2(i)} + (\epsilon_{3i}^\star - \epsilon_{3i})\mathbf{P}_{N_3(i)} + \left(L(r_i,\phi_i^\star,\epsilon_{1i}^\star,\epsilon_{2i}^\star,\epsilon_{3i}^\star) - L(r_i,\phi_i,\epsilon_{1i},\epsilon_{2i},\epsilon_{3i})\right)\mathbf{n}_i$$

Choice of ϕ_i^* controls shape

C2 : Curvature continuity constraint

$$\phi_i^* = \sum_{j \in Ngh(i)} \phi_j \Big/ Size(Ngh(i))$$



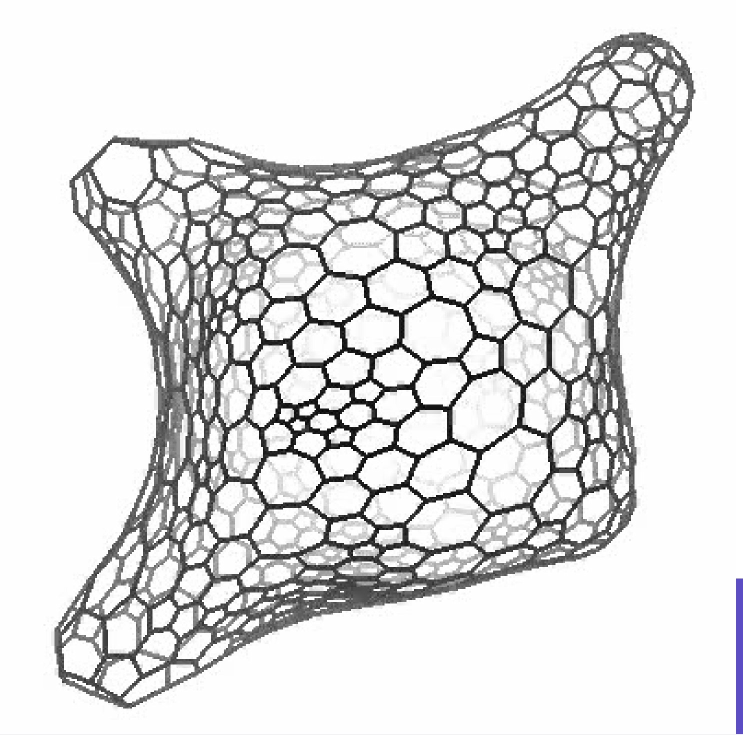
Regularization of simplex meshes

$$\sigma(\mathbf{P}_i) = (\epsilon^\star_{1i} - \epsilon_{1i})\mathbf{P}_{N_1(i)} + (\epsilon^\star_{2i} - \epsilon_{2i})\mathbf{P}_{N_2(i)} + (\epsilon^\star_{3i} - \epsilon_{3i})\mathbf{P}_{N_3(i)} +$$
$$\left(L(r_i, \phi^\star_i, \epsilon^\star_{1i}, \epsilon^\star_{2i}, \epsilon^\star_{3i}) - L(r_i, \phi_i, \epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i})\right) \mathbf{n}_i$$

Choice of ϕ_i^* controls shape

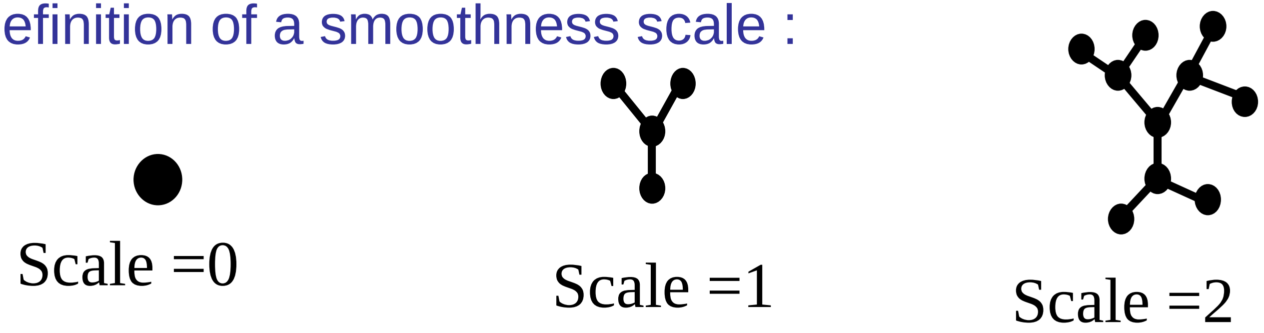
Shape constraint :

$$\phi_i^* = \phi_i^0$$



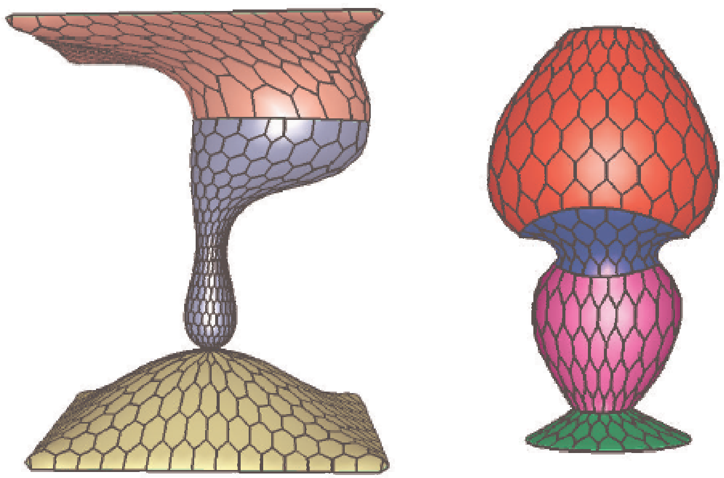
Regularization of simplex meshes

•Definition of a smoothness scale :



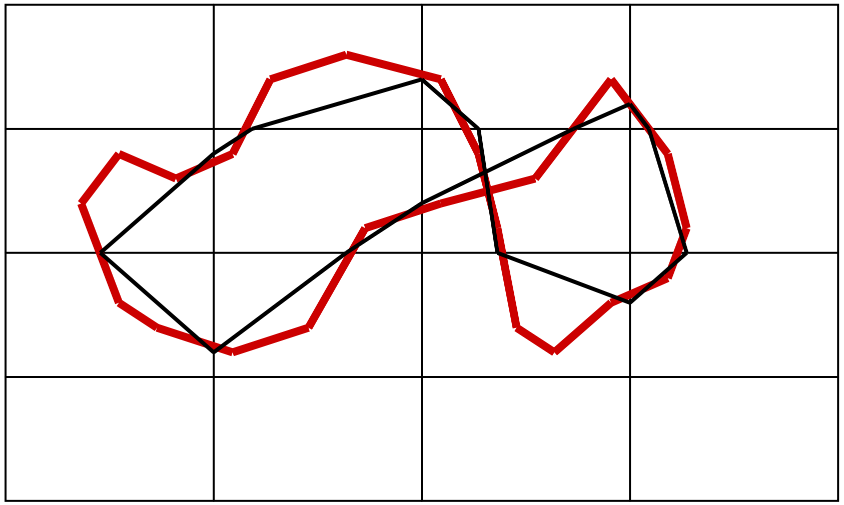
•Regularization of space curves

• Continuity between shape curves and surfaces

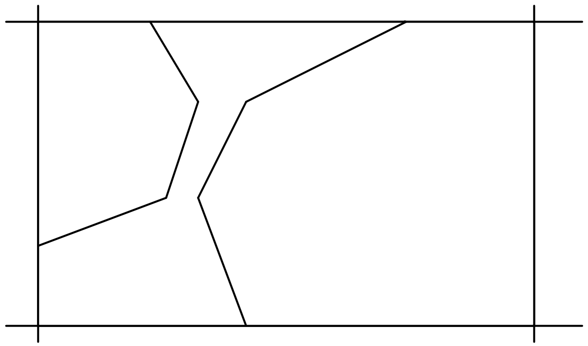


Topology Control

- Authorize topology control of planar curves
  - Use grid approximation
  - Merge or push edges
  - Handles open curves



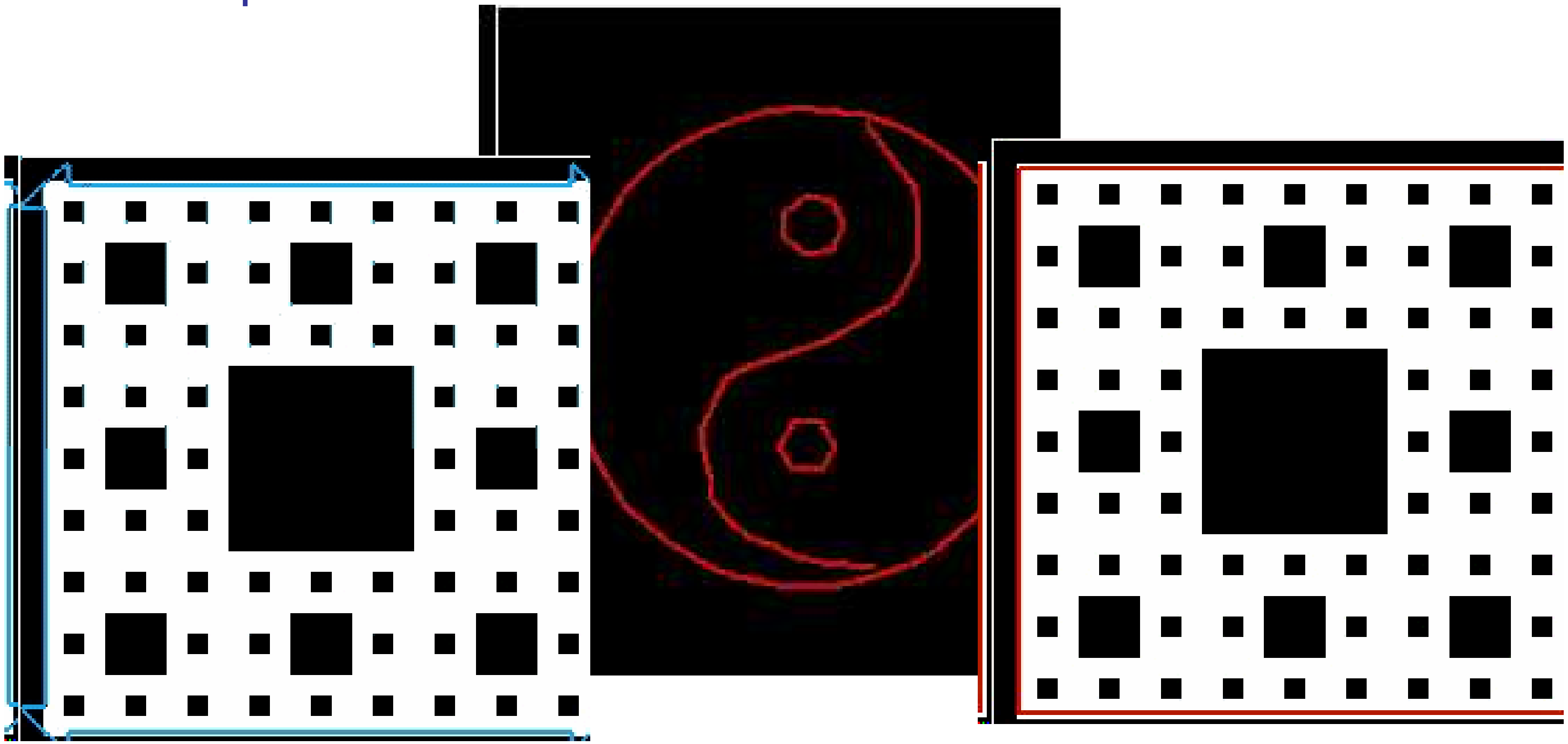
Grid approximation



Cell by cell detection

Topology control

Examples



Real time: 3,3 s

Real time: 0,42 s

Some Contributions around Image Segmentation

- Definition of External Forces
- Globally Constrained Deformations
- Initialization
- Rule-based segmentation
- 3D+T Deformable models

External Force

Use explicit Newtonian PDE

Normal internal force = displacement

$$m_i \frac{d^2\mathbf{p}_i}{dt^2} = -\gamma_i \frac{d\mathbf{p}_i}{dt} + \alpha\left(L(r_i, d_i, \phi_i^*) - L(r_i, d_i, \phi_i)\right)\mathbf{n}_i +$$

$$\alpha\left(\varepsilon_{1i}^* - \varepsilon_{1i}\right)P_{N_1(i)} + \alpha\left(\varepsilon_{2i}^* - \varepsilon_{2i}\right)P_{N_2(i)} + \alpha\left(\varepsilon_{3i}^* - \varepsilon_{3i}\right)P_{N_3(i)} + f_{\text{ext}}(\mathbf{p}_i)$$

Tangential internal force

= displacement

= displacement

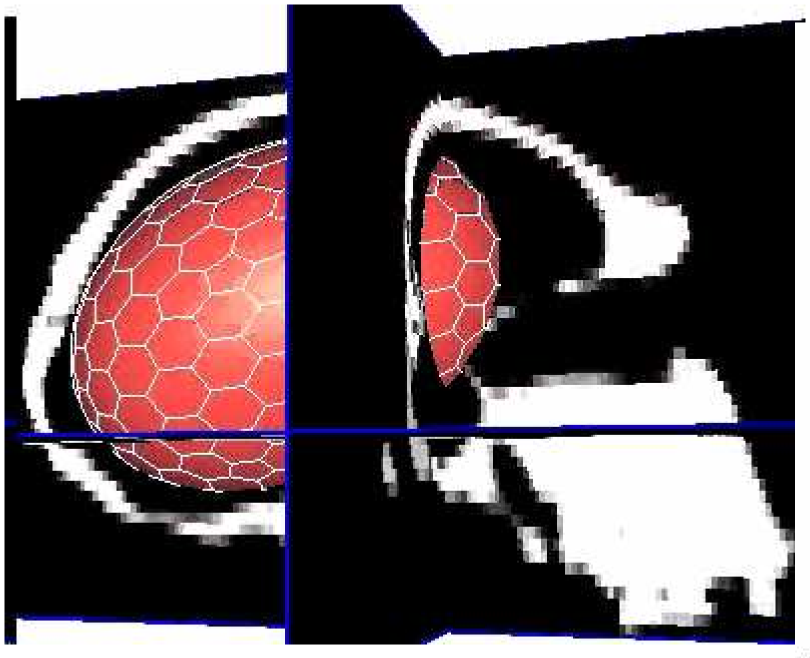
$$f_{\text{ext}}(\mathbf{p}_i) = \left(\left(\text{Closest}(\mathbf{p}_i) - \mathbf{p}_i\right) \cdot \mathbf{n}_i\right)\mathbf{n}_i$$

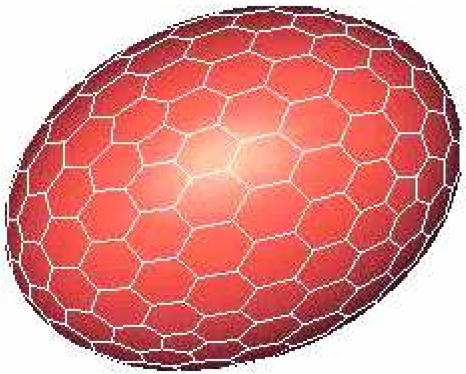
External Force

Estimation of closest boundary point

Générique

- Based on intensity and gradient





Spécifique

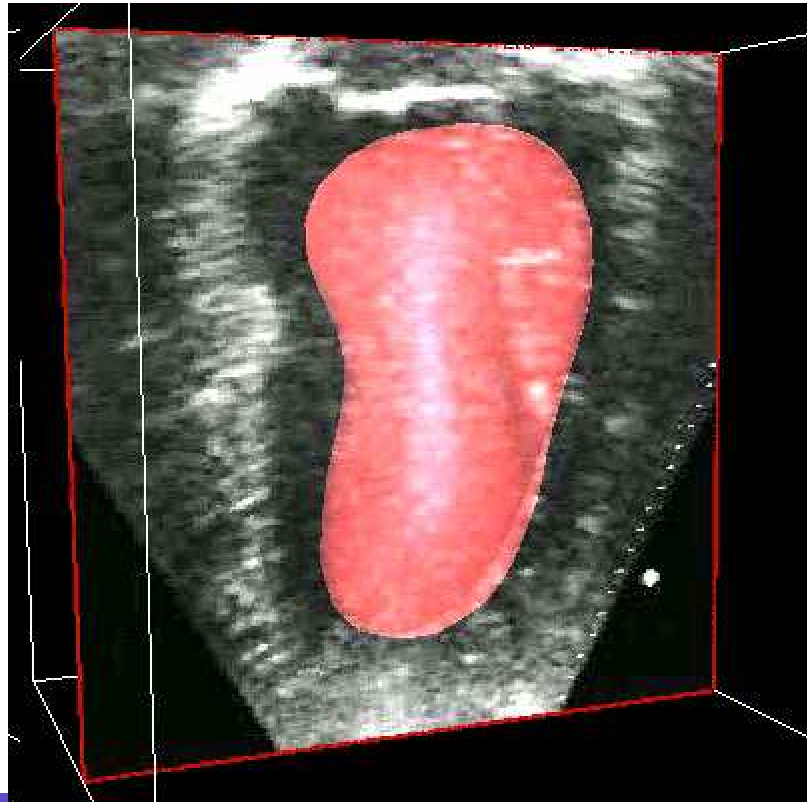
External Force

Estimation of closest boundary point

Generic

- Based on intensity and gradient
- Based on region forces

Echocardiographic
Images



Specific

Time of computation: 28 s

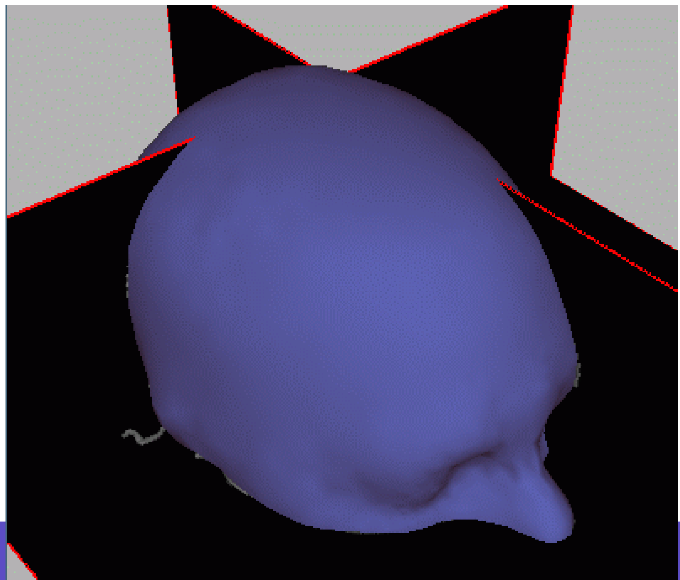
External Force

Estimation of closest boundary point

Generic

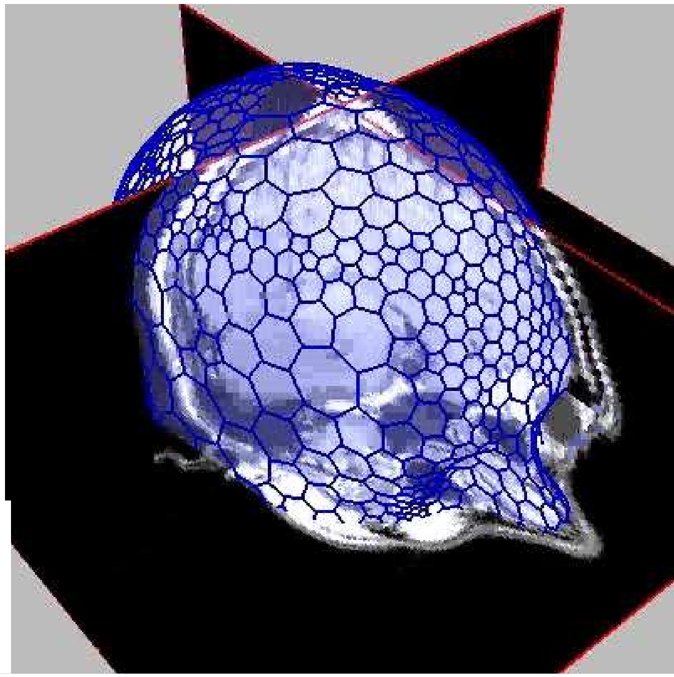
- Based on intensity and gradient
- Based on region forces
- Based on correlation of intensity profiles

Specific



Profile from CT Image

MR Image



External Force

Estimation of closest boundary point

Generic

- Based on intensity and gradient
- Based on region forces
- Based on correlation of intensity profiles
- Based on correlation of intensity block

Specific

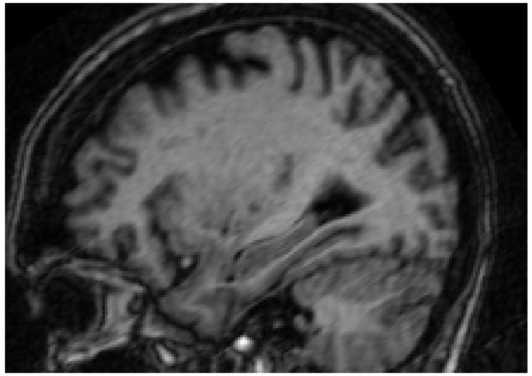
External Force

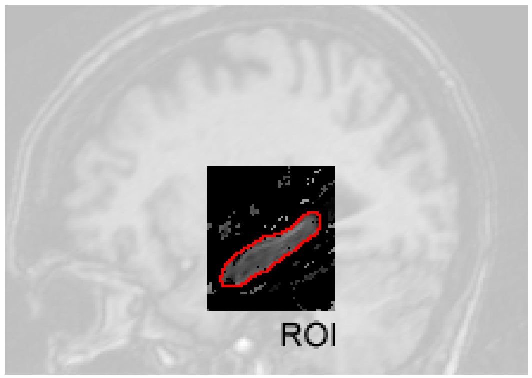
Estimation of closest boundary point

Generic

- Based on intensity and gradient
- Based on region forces
- Based on correlation of intensity profiles
- Based on correlation of intensity block
- Based on texture classification from training set
  - Linear classifier
  - SVM
  - Neural Nets

Specific

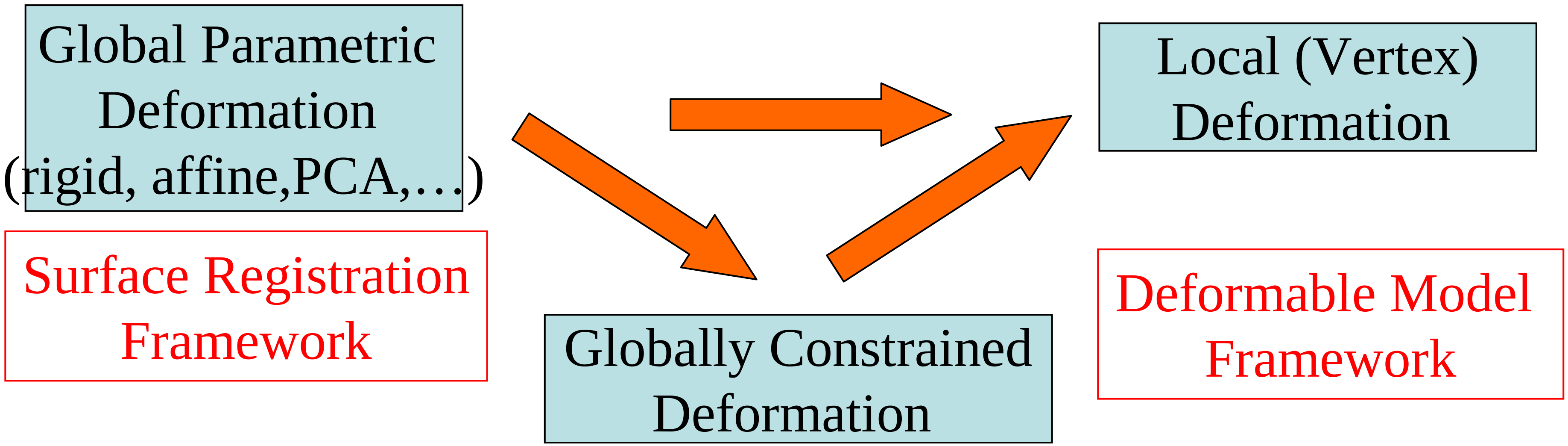




Globally Constrained Deformation

Propose a coarse to fine deformation approach in order to avoid the local minima effect

⇨ Decrease dependence on initial position

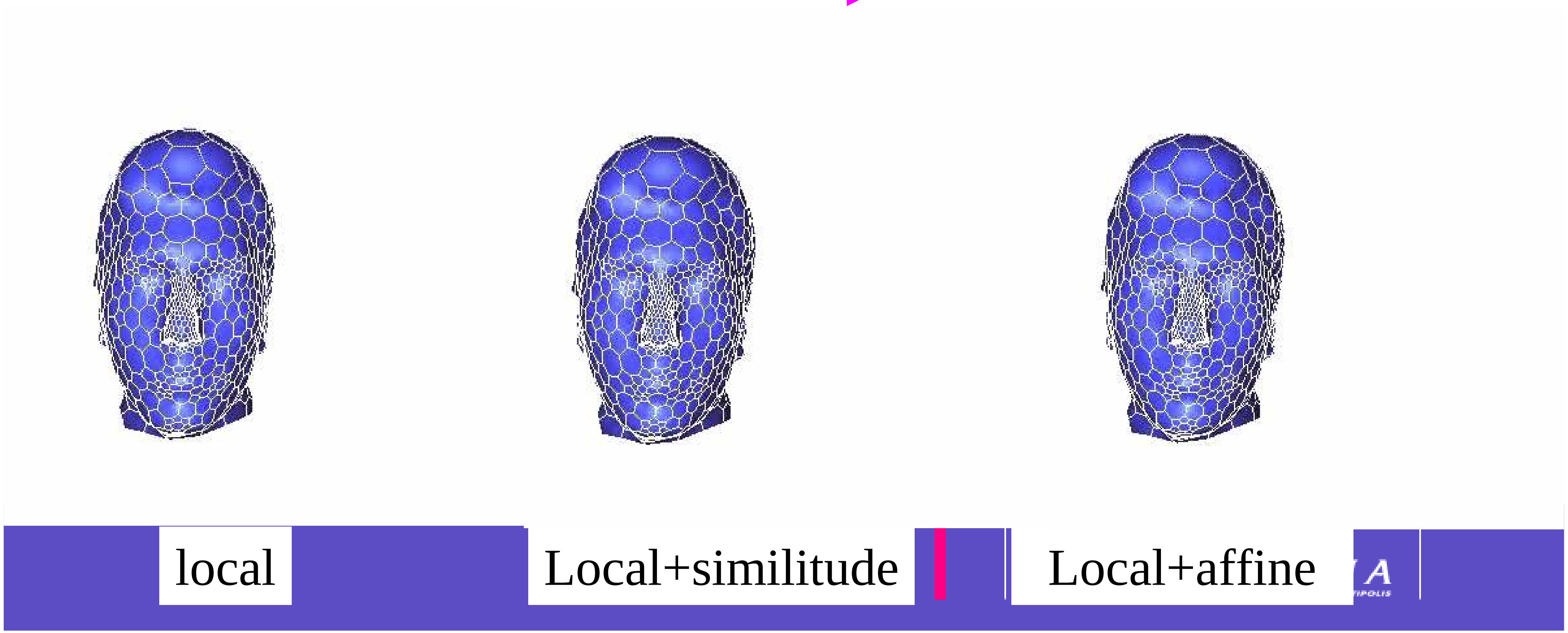


Efficient and Simple

Globally Constrained Deformation

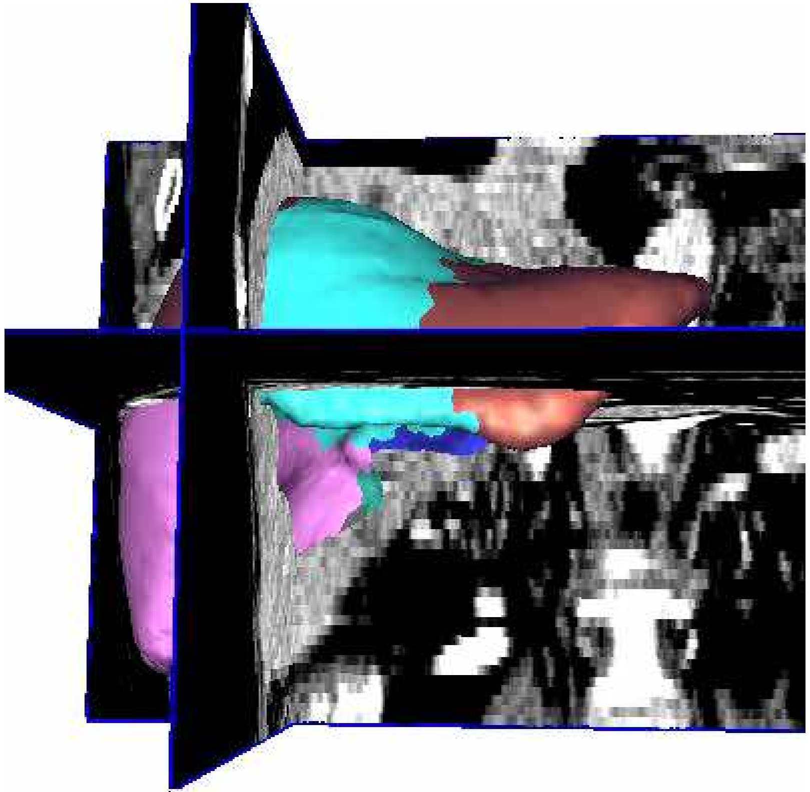
Law of Motion

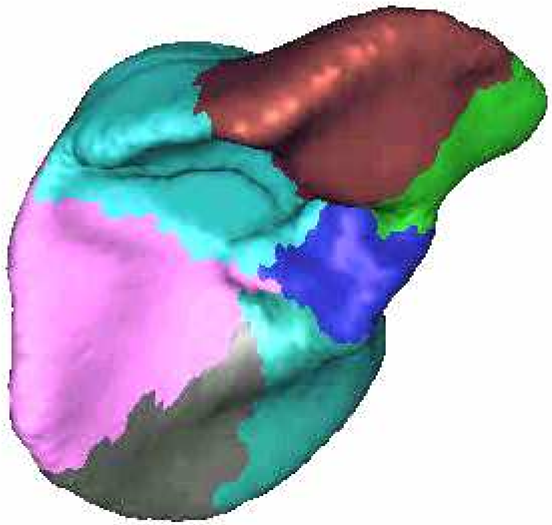
$$m_i \frac{d^2\mathbf{p}_i}{dt^2} = -\gamma_i \frac{d\mathbf{p}_i}{dt} + \lambda\left(f_{\text{int}}(\mathbf{p}_i) + f_{\text{ext}}(\mathbf{p}_i)\right) + (1-\lambda)\left(\mathrm{T}(\mathbf{p}_i)-\mathbf{p}_i\right)$$



Globally Constrained Deformation

Application to liver segmentation





Computation time : 2 mn 12 s

Extraction of Couinaud Segments

Initialisation of deformable models

From a reference shape

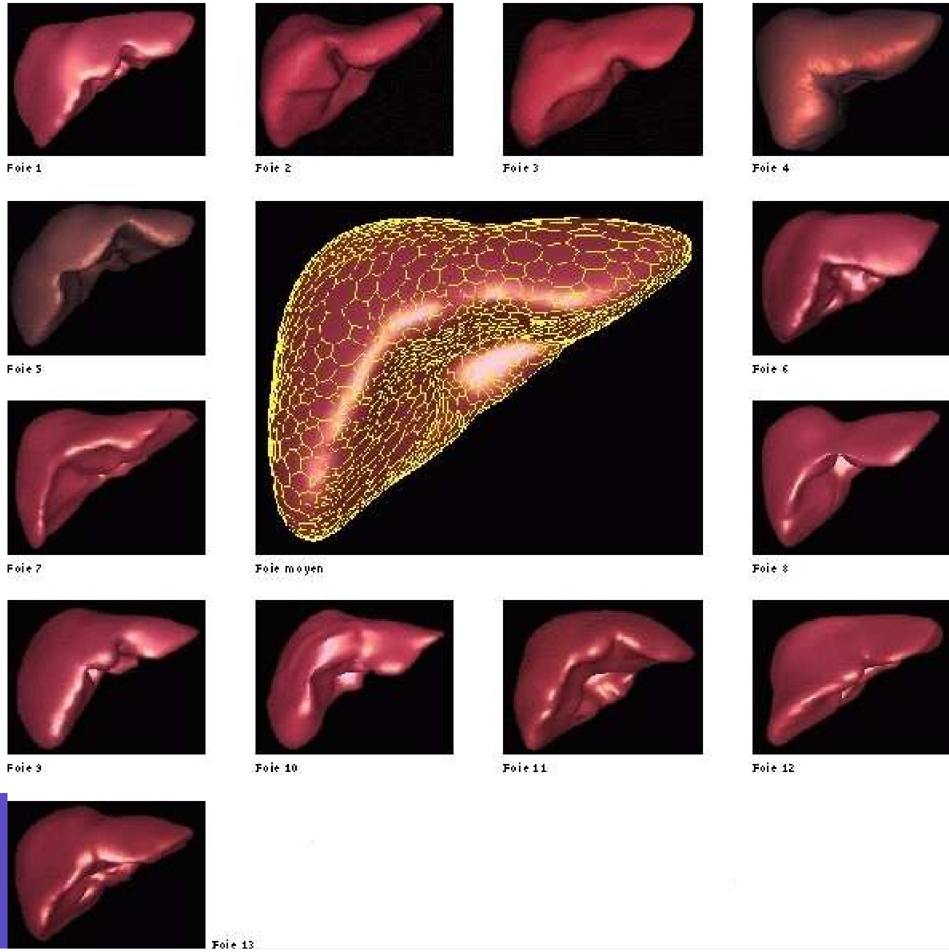
Josep … Jernigan (died August 5th

Courtesy of Univ. Hamburg

Initialisation of deformable models

From a reference shape

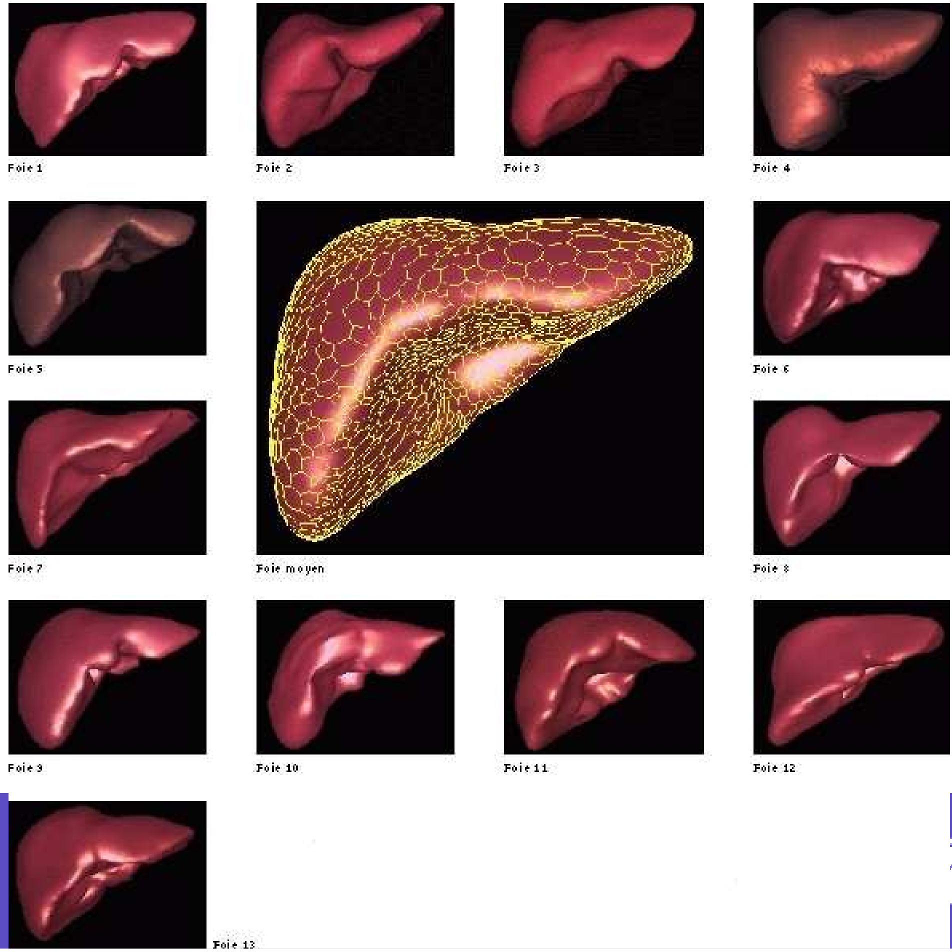
From a statistical mean shape



Initialisation of deformable models

From a reference shape

From a statistical mean shape

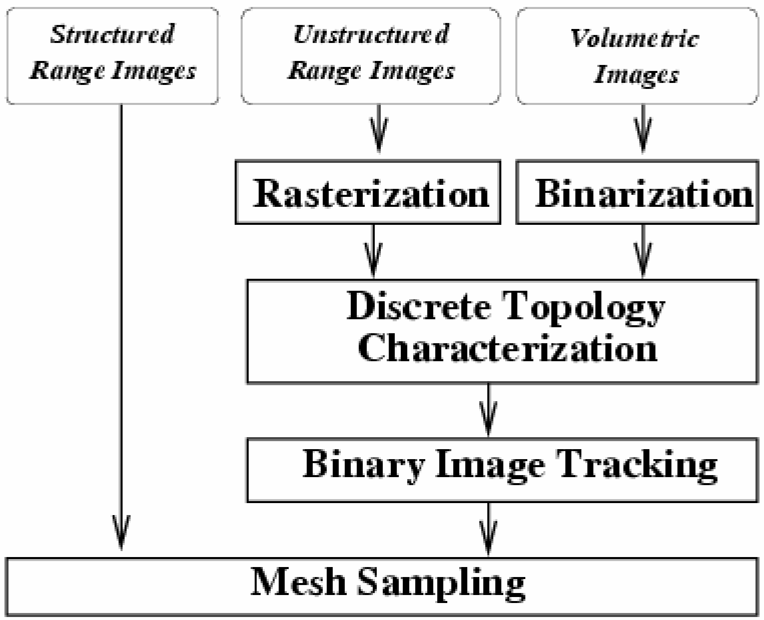


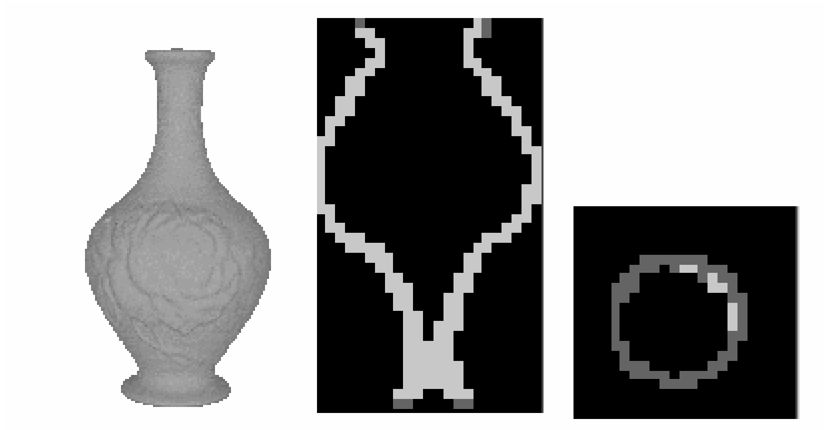
Initialisation of deformable models

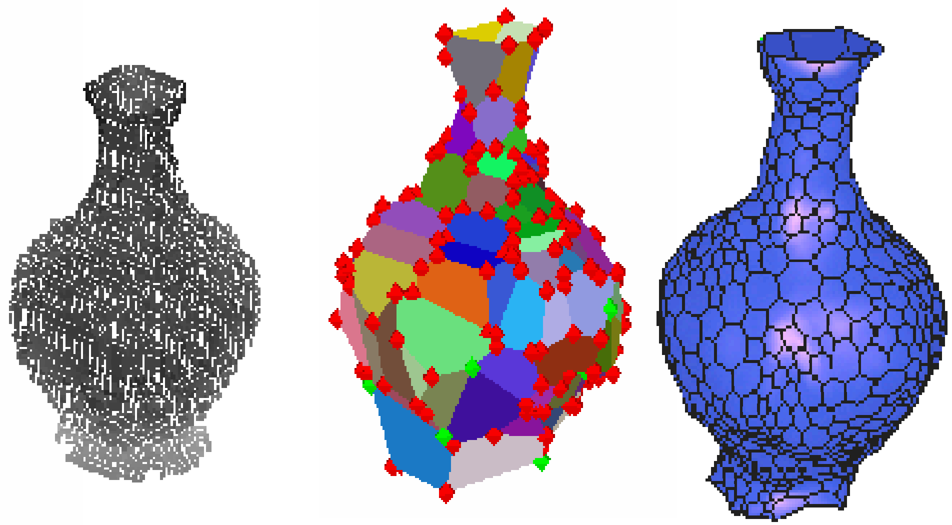
From a reference shape

From a statistical mean shape

From a set of unstructured points

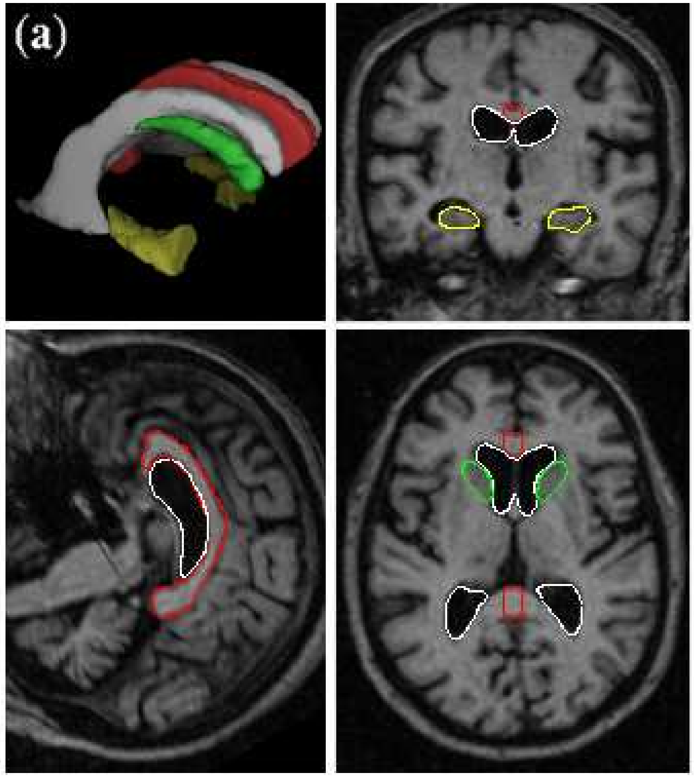




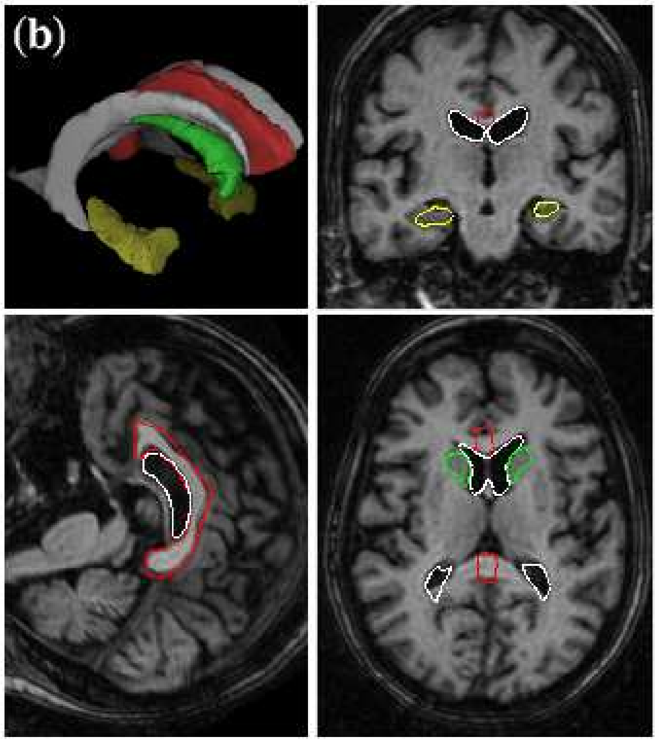


Initialisation of deformable models

- From a reference shape
- From a statistical mean shape
- From a set of unstructured points
- From a digital atlas



reference MRI with manual delineations



input MRI with initial templates

Segmentation system

Rules

- static rules [selection]
  - lateral ventricles

    high contrast ⇒ good texture map ⇒ increase texture weight

    large variability ⇒ no shape constraint
  - corpus callosum

    non-intersection with ventricles ⇒ distance constraint
  - hippocampus

    poorly defined ⇒ increased shape constraint

Segmentation system

Rules

- dynamic rules
  - coarse to fine gradient

    coarse gradient: guarantee deformation

    fine gradient: increase accuracy

  - increase locality

Meta-rules (feedback rules)

- leakage prevention

Segmentation results

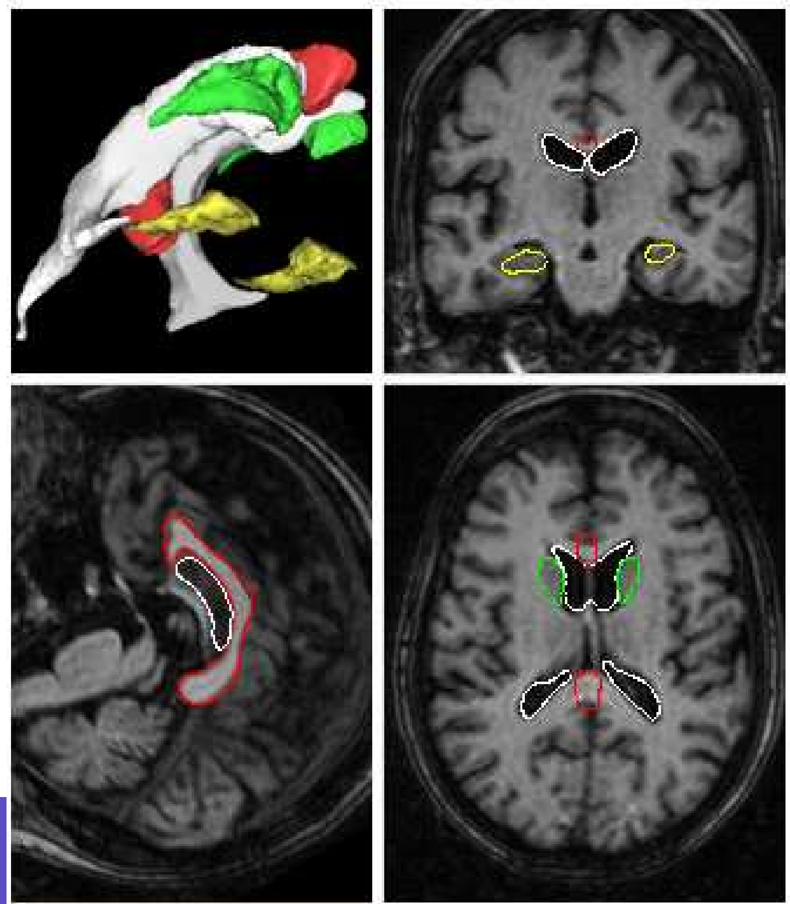
Qualitative segmentation

T1-weighted MRI, 1mm^3 resolution

– complete segmentation system

(constraints, rules, meta-rule)

→ adequate results

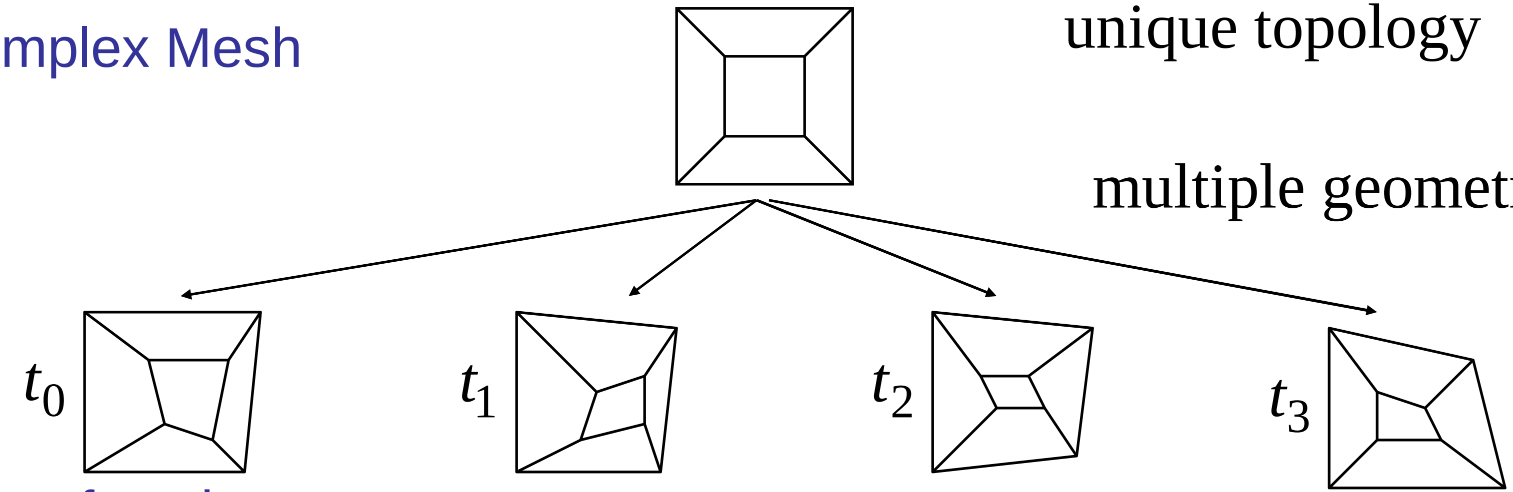


3D+T deformable models

4D Simplex Mesh

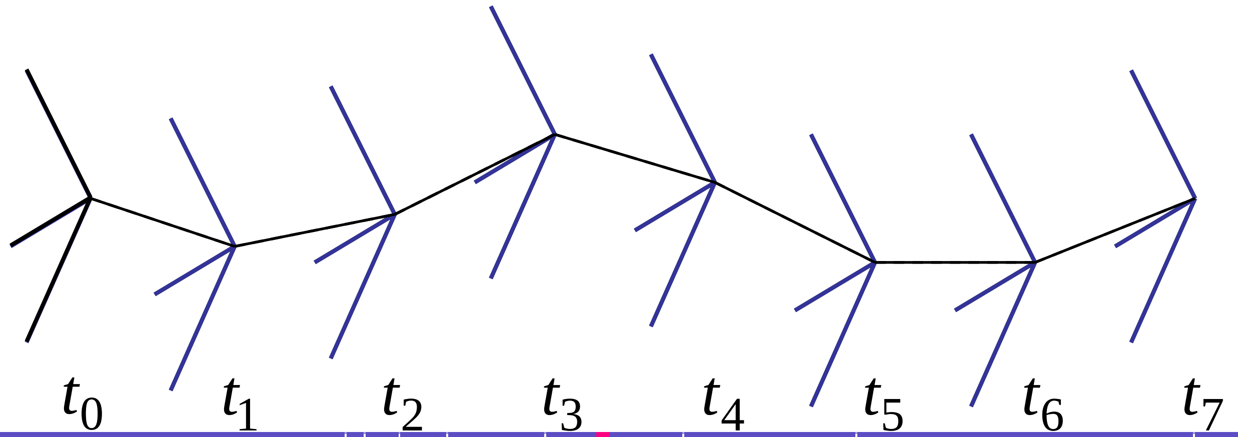
unique topology

multiple geometries



Trajectory of each vertex

$$\left\{ p_{i,t_j} \right\}_j$$

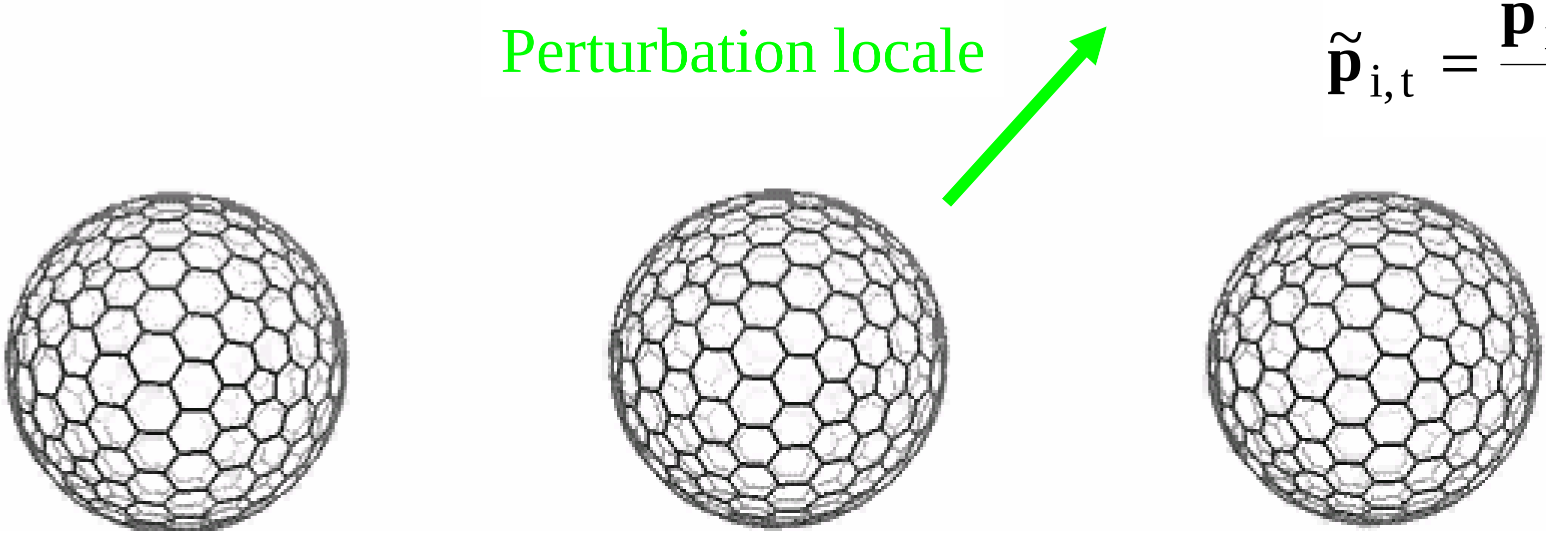


3D+T Deformable Models

Add temporal regularizing force

$$m_i \frac{d^2 \mathbf{p}_{i,t}}{dt^2} = -\gamma_i \frac{d\mathbf{p}_{i,t}}{dt} + f_{int}(\mathbf{p}_{i,t}) + f_{ext}(\mathbf{p}_{i,t}) + f_{time}(\mathbf{p}_{i,t})$$

$$\tilde{\mathbf{p}}_{i,t} = \frac{\mathbf{p}_{i,t+1} + \mathbf{p}_{i,t-1}}{2}$$



T-1 T T+1

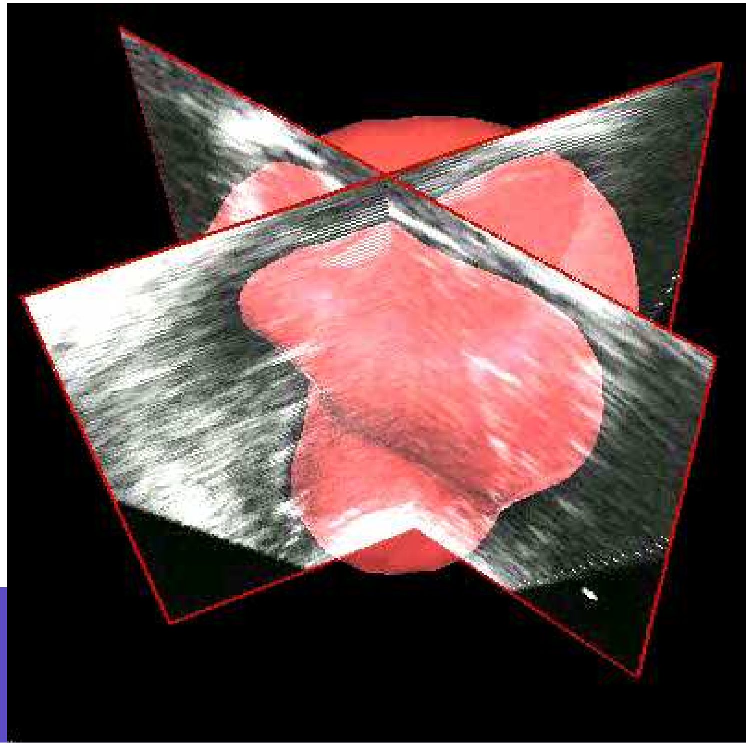
3D+T Deformable Models

Validated on a synthetic time series of SPECT images

Extended with trajectory constraint

Included with the globally constrained deformation

Application with 4D echocardiography



3D+T Deformable Models

Application to cardiac image analysis