

Analyse d'Images Médicales et Modélisation: de l'acquisition à la quantification

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Bone image HRX











MRA Carotid



Difficulties

- Images = Partial measurements
- Objectives: Recover the truth
 - shapes, functions...
 - normal and abnormal patterns

Inverse problem:
 Not a unique solution
 Stability upon the data



From ill-posed to well-posed The image segmentation example

- Regularization (smoothness constraint)
- Adding prior information:
 - Shape constraints: average shape, topology, shape statistics...
 - Static and dynamic properties
 - Other functional properties
 - Appearance model (image)



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The Modeling perspective



From Hunter & Borg Nature Rev, 2003 (Physiome & VPH projects)





Patient specific cardiac modeling



Available data





MR imaging



Standard multi-slice cine images

→ Human & small animal



Dynamic cardiac segmentation





- Objective:
 - segmentation and tracking of the heart in temporal image sequences (MRI)
 - Characterizing the shape and dynamics of normal and pathological hearts



The Deformable Elastic Template (DET)

• Principle



Reference a priori model



Mailleur GHS3D, Gamma Project, INRIA



DET Patient specific model adaptation

Elastic deformation





 Elastic solid under constraints : – Equilibrium equation

$$\begin{cases} \operatorname{div} \boldsymbol{\sigma} = \mathbf{0} & \operatorname{in} \Omega_0 \\ \boldsymbol{\sigma}_n = f & \operatorname{on} \partial \Omega_0 \end{cases}$$

– Potential energy

$$E(u) = \frac{1}{2} \int_{\Omega_0} \varsigma^T(u) \epsilon(u) \, dx - \int_{\delta\Omega_0} f^T \cdot u \, ds$$

$$E_{elastic} E_{image}$$

$$E_{elastic} = \frac{1}{2} \int_{\Omega} \mu \nabla u^T \nabla u + (\lambda + \mu) \operatorname{div}(u) \operatorname{div}(u) \, d\Omega$$

With λ , μ the Lamé Coefficients



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- Optimization: FEM

 Partitioning the domain in elements
 Linear basis functions
 - Solving the system
 - Algorithm M1: incremental load

$$\mathbf{M1} \quad \begin{cases} \mathbf{u}^{k+1} - \Delta t \operatorname{div} \sigma(\mathbf{u}^{k+1}) = \mathbf{u}^{k} \operatorname{dans} \Omega_{0} \\ \sigma_{n}(\mathbf{u}^{k+1}) = f(\mathbf{I} + \mathbf{u}^{k}) \operatorname{sur} \partial \Omega_{0} \end{cases}$$

$$\mathbf{KU} = \mathbf{F}$$

• FEM solution: evolution equation

$$\frac{d\mathbf{U}}{dt} + \mathbf{KU}(t) = \mathbf{F}(\mathbf{U}(t))$$

$$\mathbf{U} = (u_1, u_2, u_3, \dots u_N)$$

$$(\mathbf{I} + \Delta t \mathbf{K})\mathbf{U}^{k+1} = \mathbf{U}^k + \Delta t \mathbf{F}(\mathbf{U}^k)$$



DET story

- 2D linear static DET : [PhD thesis F. Vincent, 2001]
- 3D linear static DET, biventricular model : [PhD thesis Q-C. Pham, 2002]
- Non-linear static DET, [PhD thesis Y. Rouchdy, 2005] (Collab. ICJ, J. Pousin)
- Dynamique DET, [PhD thesis J. Schaerer, 2008] (Collab. ESIEE, L. Najman, J. Cousty)









Non linear algorithm [Rouchdy, 2005]
 To avoid the linearization of the def tensor

$$\begin{cases} div\sigma(u(\lambda)) = 0 & \text{in } \Omega\\ \sigma(u(\lambda)) \cdot n = \lambda f(u(\lambda)) & \text{on } \partial\Omega \end{cases}$$

Where λ [0,1] is an evolution variable – With an explicit Euler scheme:

$$\mathbf{A}^{k}\mathbf{U}_{k+1} = \mathbf{A}^{k}\mathbf{U}_{k} + (\lambda_{k+1} - \lambda_{k})\mathbf{F}(\mathbf{U}_{k})$$

with
$$\mathbf{A}^{k} = \mathbf{K}^{k} - \lambda_{k}\mathbf{D}^{k}$$

Collab. Inst. C. Jordan, INSA Lyon MATH-STIC CNRS project



• Border constraint: $f(\mathbf{I} + u) = 0$

 Singular perturbation approach [Schaerer, 2008]

$$(\Delta t e^{-\beta k} \mathbf{K} + \mathbf{I}) \mathbf{U}^k = \Delta t F(\mathbf{U}^{k-1}) + \mathbf{U}^{k-1}$$

With Δt the time step and β a parameter controlling the decrease

 If the force field derive from a potential and is Lipschitz then the algo converges

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Multiresolution meshes





Impact of the non linear DET





Maillage initial de boule $(\approx 6000 \text{ points})$

Maillage déformé



 Critère de qualité: rayon de la sphère inscrite au tétraèdre sur la longueur de sa plus grande arrête, compris entre 0 et 1

	Cube linéaire	Cube non-linéaire
Sans multirésolution		
Temps de calcul	54s	1m25s
Qualité moyenne	0.58	0.61
Qualité minimale	0.10	0.17
Multirésolution à 3 niveaux		
Temps de calcul	26s	46s
Qualité moyenne	0.58	0.61
Qualité minimale	0.13	0.17

 \Rightarrow L'algorithme non-linéaire permet une meilleure stabilité numérique



Mesh Quality for FE methods

- Discretization error
- Interpolation error
- Matrix conditionning





Reconstructing 3D meshes from voxels J. Dardenne thesis

• Domain partitioning with frontier preservation (energy minimization approach)



J. Dardenne, S. Valette et al. Variational tetraedral mesh generation from discrete volume data. *The Visual Computer, pp (in-press), 2009.*



Adaptive mesh density through a density map







volume data. The Visual Computer, pp (in-press), 2009.

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DET automatic initialization

 Looking for a 3D affine transform T which minimizes:

$$J(p) = \sum_{i=1}^{N_{c}} d_{n}^{2}(T(p, \mathbf{x}_{i})) + \sum_{i=1}^{N_{nod}} (I(T(p, \mathbf{x}_{i})) - I_{nod}(\mathbf{x}_{i}))^{2}$$
Where
$$p = (t_{x}, t_{y}, t_{z}, r_{x}, r_{y}, r_{z}, s_{x}, s_{y}, s_{z}, sh_{xy}, sh_{xz}, sh_{yz})$$
And
$$T = T_{r} \circ S \circ R$$

- Based on endocardial contours
- Multi-random-start simplex
 optimization method



- Initialization evaluation
 - One ED 3D image
 - Comparison to a manual established reference

$$\left\|p_{ideal}-p\right\|^2 < \Delta_p$$

10-4000 random starts
200 registrations to estimate the error rate for

each configuration

te for







 \rightarrow The proposed approach offers the best compromise



Some results

Mouse Images 7T MRI(FLASH sequence FOV=25 mm2, 256 ×256 pixels, slice thickness=1 mm), cardiac freq. = 450 bpm.



DET Spatio-temporal Model

- Assumptions
 - Continuous & periodic motion
- Simplified fundamental equation of dynamics :

$$\mathbf{D}\dot{\mathbf{U}}(t) + \mathbf{K}\mathbf{U}(t) = \mathbf{F}\left(\mathbf{U}(t), t\right)$$

Trajectory representation (Fourier)

$$\mathbf{U}(t) = \sum_{n=0}^{N} \mathbf{A}_n \cos(\frac{2\pi n}{N}t) + \mathbf{B}_n \sin(\frac{2\pi n}{N}t)$$



Implementation of the non-linear problem

 Pseudo instationnary scheme: a series of linear problems

$$\begin{cases} \frac{d\mathbf{U}}{d\tau} = \mathbf{F}(\mathbf{U}) - \mathbf{AU} \\ \mathbf{U}(0) = 0. \end{cases}$$

$$(\frac{1}{\Delta \tau} + \mathbf{A})\mathbf{U}^{\tau} = \mathbf{F}(\mathbf{U}^{\tau-1}) + \frac{1}{\Delta \tau}\mathbf{U}^{\tau-1}$$

 \rightarrow Existence, uniqueness and asymptotic behavior with respect to τ can be demonstrated

[Schaerer et al., in revision]

1D+time illustration

 $\alpha u'(t) + ku(t) = f(t)$



Fig. 1. Sample 1D results: (a) Target signal (green curve) and initialization (U = 0), (b) Results without filtering or damping, (c) Results with damping but no filtering (d=0.2, k=1), (d) Results with damping and filtering (d=0.2,k=1 and 8 harmonics)



- 2D Implementation

 Initial myocardial model: annulus
 - Constraint field from images
 - Gradient + GVF, but
 - Temporal jittering
 - Local lack of data
 - Morphological pre-segmentation as a constraint (PhD thesis J. Cousty, ESIEE) + GVF





Dynamic DET segmentation Results

- MRI in vivo Sequences
 - Human cardiac MRI database at <u>http://laurentnajman.org/heart</u>
 - 18 cases
 - multi-phase, multi-slice cine-MRI
 - 5-10 slice levels 256x256
 - ~1mm in plane, 5-10mm slice thickness
 - 15-30 phases
 - IMPEIC project: 'Initiative Multicentrique pour une Plateforme d'Evaluation en Imagerie Cardiaque' (supported by GDR STIC-Santé)





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Segmentation with pre-segmentation

GVF based Segmentation

Harmonic order impact



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Dynamic DET motion tracking Results

- Synthetic 2D MRI Sequences
 - Spatio-temporal reference heart model [Clarysse, MEDIA 2000]
 - Simulated MRI Sequence [Delhay, submitted]
 - Parameters
 - Model: normal/patho
 - Image: variable noise level





Simulated Sequence 'normal subject', ~ basal level





Radial displacement error (mm)





Conclusions on DET model

- Generic concept
 - Adaptable to various geometries :Tested on 3D US imaging
 - Dynamic DET: motion tracking in Cine MRI
 tagged
- Still...
 - Parameter tuning
 - Template initialization
- Remarks
 - Computing a convenient force field (modality dependent)
 - Simplifying image information
 - \rightarrow low level processing
 - → multi-resolution approaches



A Priori Statistical dynamical model

Learning based static model (4 chambers)

• 15 healthy subjects

[Lötjönen et al., 2004]

• Short Axis + Long Axis slices (End- Diastole)

Set of *n* geometrical models whose points are spatially coheren

$$\bar{\mathcal{S}} = \frac{1}{n} \sum_{p=1}^{n} \mathcal{S}(p) = \frac{1}{n} \sum_{p=1}^{n} \left(\boldsymbol{x}^{i,p} \right)_{1 \le i \le m}$$



Semi-landmarks number = 2086



Collab. J. Lötjönen, HUT & VTT, Finland 🥻

Inter-individual variability

Subject 2



Subject 15

Learning based dynamic model [Delhay et al. Cinc 05]

Atlas transport through the sequence

For each subjects: sequential non-rigid registrations [Lötjönen and Mäkelä, 2001]

+

Manual corrections



Trajectory normalisation for 15 healthy volunters, ~2100 pseudo-landmarks over the whole heart









Mean dynamical model



Landmark variability modeling
 Parzen Windowing
 Only one parameter

Continuous probability density function (PDF)

$$p(\boldsymbol{x}^{i}(t)) = \frac{1}{nh} \sum_{p=1}^{n} K\left(\frac{\|\boldsymbol{x}^{i}(t) - \boldsymbol{x}^{i,p}(t)\|^{2}}{h}\right)$$

 \mathcal{N} : number of subjects in the data set

 $\boldsymbol{x}^{i,p}(t)$: Coordinates of the landmark *i* at time *t*

- K : Gaussian kernel
- h : Kernel size



A priori driven segmentation A priori regularizing term C

$$\mathcal{J}(I_c, I_s, \boldsymbol{\varphi}) = \mathcal{A}(I_c, I_s, \boldsymbol{\varphi}) + \alpha \mathcal{R}(\boldsymbol{\varphi}) + \gamma \mathcal{C}(\boldsymbol{\varphi})$$
$$\mathcal{C}(\boldsymbol{\varphi}, h) = \frac{1}{2} \sum_{i=1}^m (1 - p(\boldsymbol{x}^i(t_j), h))^2$$

Jacobian of the transformation

$$\frac{\partial \mathcal{C}_i(\boldsymbol{\xi}, h)}{\partial \boldsymbol{\xi}} = \left(1 - p(\boldsymbol{\varphi}_{t_0; t_j}(\boldsymbol{x}^i(t_0), \boldsymbol{\xi}), h) \right).$$
$$\times J \times \frac{\partial p(\boldsymbol{\varphi}_{t_0; t_j}(\boldsymbol{x}^i(t_0), \boldsymbol{\xi}), h)}{\partial \boldsymbol{x}}$$

Derivative of the Parzen function



Conclusions on Learning based models

Generic concept

- Adaptable to various anatomical structures
- Adaptable to deformable structures
- But
 - Construction of the a priori model is laborious
 - Difficulties to construct large sample sets
 - Ilmitation in shape variations (normal & abnormal)
- Artificial enlargement [Koikalainen, IEEETMI-2008]
 - Partitioning the structure into separate parts
 - Non-rigid local perturbations
- Artificial smoothness
 - Covariance matrix to induce smoothness to def. modes
 - PCA + FEM



Method's evaluation : a whole numeric approach 3D virtual model and imaging



http://www.cst.com/





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Breathing thorax & beating heart model



[Haddad, PhD thesis 2007], [Haddad et al, IEEE EMBS, 2007]



Simulated images, MRI Simulator SIMRI, CREATIS-LRMN [Benoit-Cattin et al, JMR,05]



PET simulation with SORTEO (Cermep, Lyon): Simulated emission PET images for healthy and ischemic models (hypocaptation of glucosis)

Healthy model

Ischemic model (F-18 collecting in the myocardium with 40% of its initial value)

Axial slice

Sagittal slice









 → Simed project (P. Clarysse – E. Promayon)
 Simulation en Imagerie Médicale pour le Diagnostic et la Thérapie





→ Virtual Physiological Human European NOE





Collaborations / Support

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• Thank you!



