

From Biomedical Images To Virtual Personalized Physiological Patients

Let's Imagine the Future

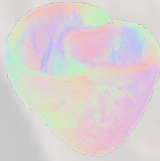
for Jean-Pierre Banâtre

Rennes

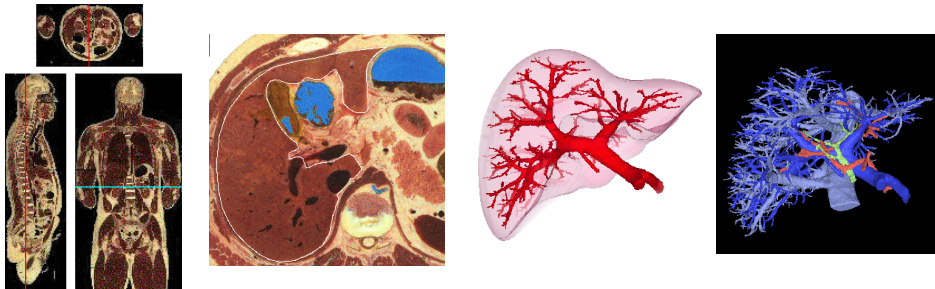
9 November 2012

Nicholas Ayache

<http://www-sop.inria.fr/Asclepios/>



The Visible Human Project-NLM 1996-2002



- Anatomy only
- 1 subject
- No function
- No variability

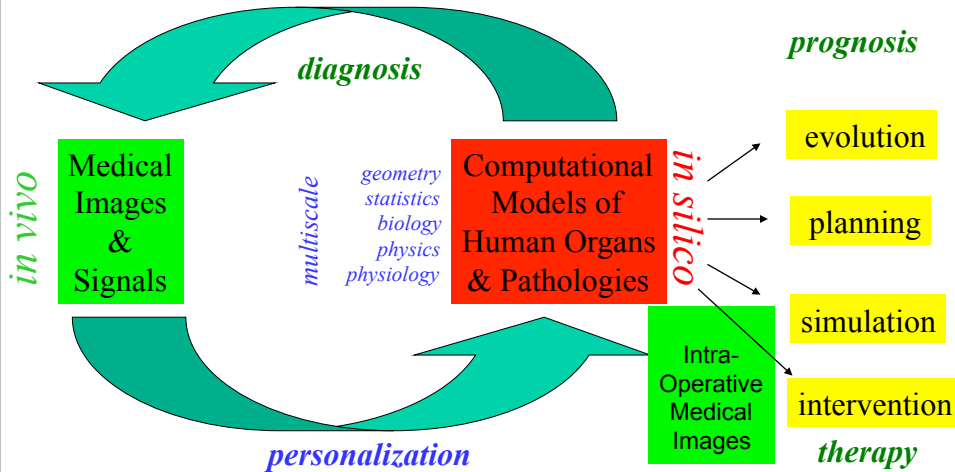
N. Ayache
Rennes 9 Nov. 2012

From Biomedical Images to Virtual
Personalized Physiological Patients



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Oct 2004 -2012 : Virtual Personalized Physiological Patient



•Computational Models for the Human Body, Elsevier, July 2004. Ayache, N, Ciarlet P., Lions JL(Editors)
 •Towards Virtual Physiological Human (VPH), European White Paper , Nov. 2005. Ayache, N, Frangi A, Hunter P, Hose R, Magnin I, Viceconti M. et al., The Virtual Physiological Human, Interface Focus, Royal Society 2011, Coveney P, Diaz V, Hunter PJ, Kohl P, Viceconti M

April 2012-17

erc MedYMA
Advanced Grant 291080

- Push forward Statistical & Biophysical Models
- *Analysis and Simulation of Medical Dynamic Images*
- To improve *diagnosis, prognosis, therapy*



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Personalized Physiological Patients

inria
informatics mathematics

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Clinical Applications



- Computational Oncology
 - **Brain tumors** (gliomas), Liver, etc...
- Computational Neurology
 - **Alzheimer's Disease**, Multiple Sclerosis,...
- Computational Cardiology
 - **Heart Failure, Arrhythmia**,...

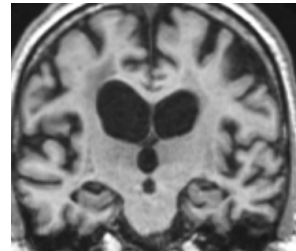
Clinical Applications



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Alzheimer's Disease

- Most common form of dementia
- 18 Million people worldwide
- Prevalence in advanced countries
 - 65-70: 2%
 - 70-80: 4%
 - 80 - : 20%



baseline

- If onset was delayed by 5 years, number of cases worldwide would be halved

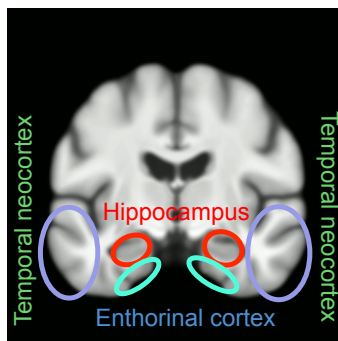
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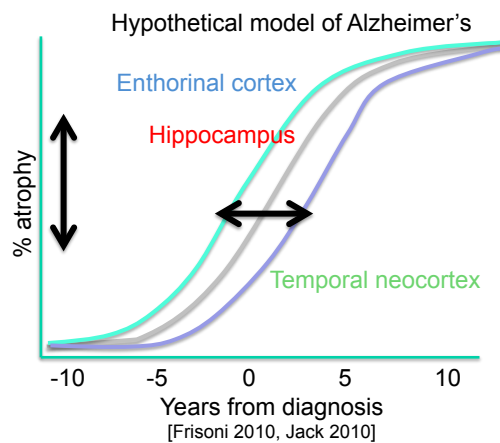


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Longitudinal atrophy in Alzheimer's disease



[Lorenzi 2011]



Discovery

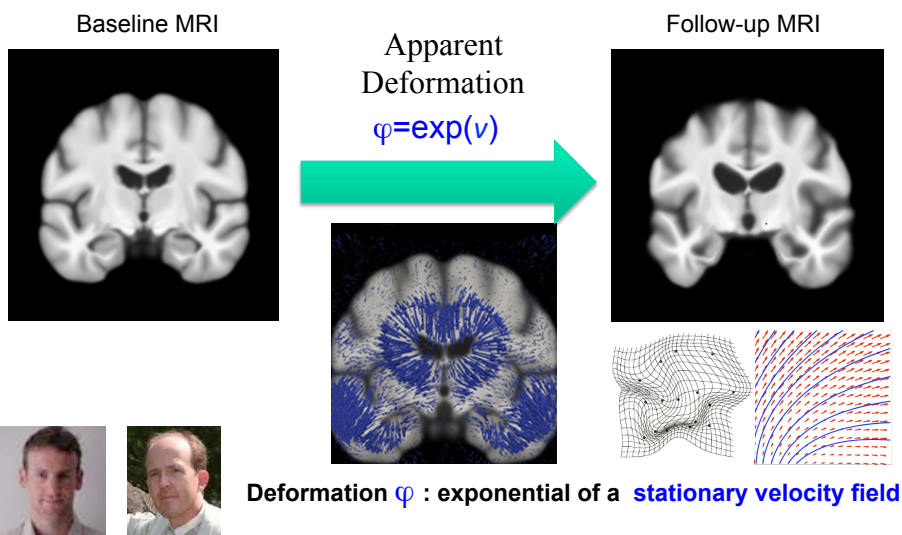
Where, when?

Quantification (clinical trials, diagnosis)

How much?

M Lorenzi, N Ayache, X Pennec. Regional flux analysis of longitudinal atrophy in Alzheimer's disease. MICCAI 2012

Non-linear registration for longitudinal analysis



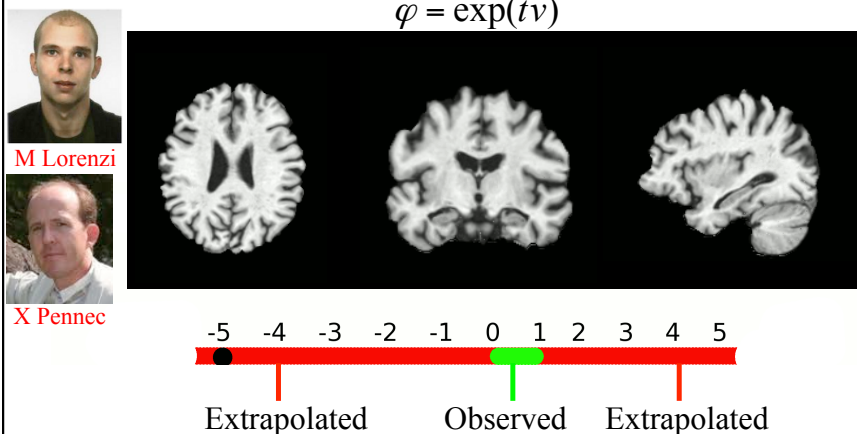
T Vercauteren, X Pennec, A Perchant, and N Ayache, *Diffeomorphic Demons: Efficient Non-parametric Image Registration*. NeuroImage, 2009

Generative Model of Brain Atrophy for AD

Average evolution from 70 AD patients (ADNI data)

Measure SVF: 1 year Extrapolation: ± 7 years

$$\bar{\varphi} = \exp(t\bar{v})$$



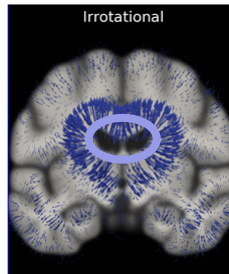
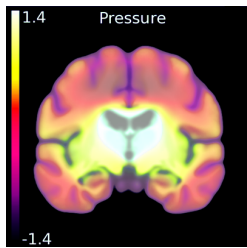
[Lorenzi, Ayache, Pennec IPMI 2011]

Inria
informatics mathematics

Analysis of Stationary Velocity Field

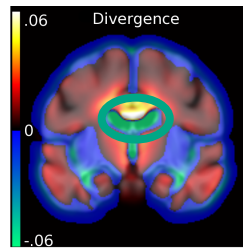
Discovery

“Virtual” Pressure p
 Defines **sources and sinks**
 of the atrophy process



Quantification

Divergence $\nabla \cdot \nabla p$
 Defines **flux** across
 expanding/contracting regions



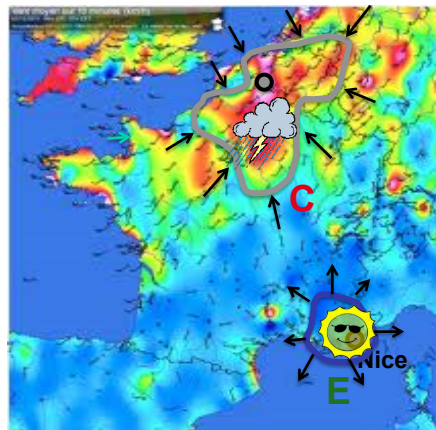
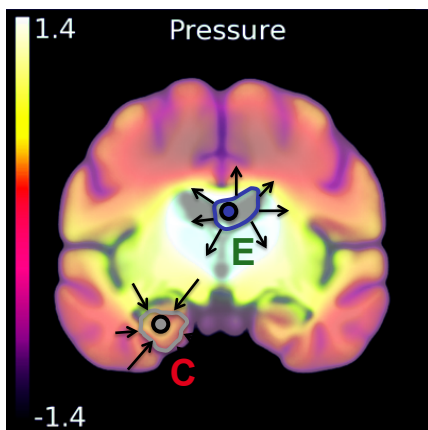
Divergence Theorem

$$\oint_{\partial V} \nabla p \cdot n \, dS = \int_V \nabla \cdot \nabla p \, dV$$



M Lorenzi, N Ayache, X Pennec. Regional flux analysis of longitudinal atrophy in Alzheimer's disease. MICCAI 2012

Pressure Extrema

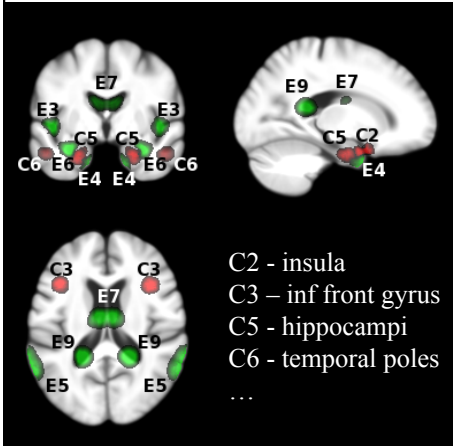


- Step1. local maxima (sources) and minima (sinks) of pressure field
- Step2. Expansion and Contraction: areas of maximal outwards/inwards flux

M Lorenzi, N Ayache, X Pennec. Regional flux analysis of longitudinal atrophy in Alzheimer's disease. MICCAI 2012

Discovery

Group Analysis



ADNI dataset

(<http://adni.loni.ucla.edu/>)

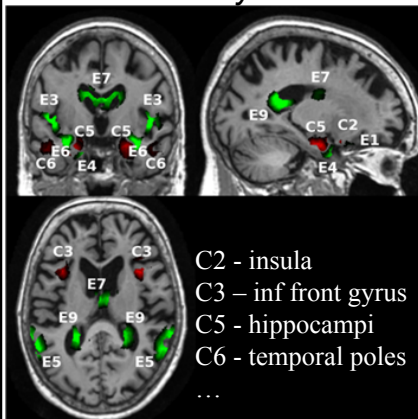


- 20 Alzheimer's patients
- 1 year follow-up
- two time points

M Lorenzi, N Ayache, X Pennec. Regional flux analysis of longitudinal atrophy in Alzheimer's disease. MICCAI 2012

Quantification

Subject Specific Analysis



Probabilistic masks in the subject space

MICCAI 2012 grand Challenge

Effect size on Atrophy Measure

Group	six months	one year	two years
INRIA - Regional Flux	1.02	1.33	1.47

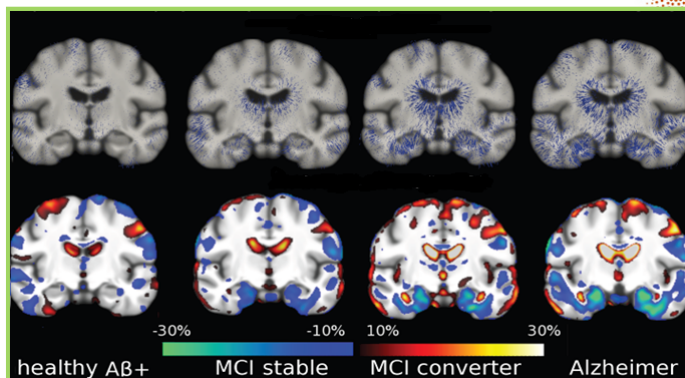
Ranked 1st & 2nd on Hippocampus

Major competitors:

- Freesurfer (Harvard, USA)
- Montreal Neurological Institute, Canada
- Mayo Clinic, USA
- University College of London, UK
- University of Pennsylvania, USA

M Lorenzi, G B. Frisoni, N Ayache, and X Pennec. Probabilistic Flux Analysis of Cerebral Longitudinal Atrophy. MICCAI workshop NIBAD 2012

Future Challenges



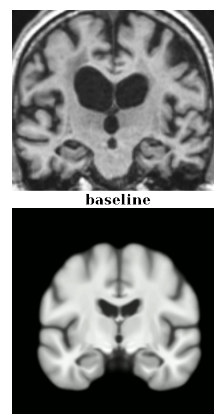
- Biomarkers for early detection of abnormal atrophy patterns and efficient follow-up of treatment

M Lorenzi, N Ayache, X Pennec G B. Frisoni, for ADNI. Disentangling the normal aging from the pathological Alzheimer's disease progression on structural MR images. 5th Clinical Trials in Alzheimer's Disease (CTAD'12), Monte Carlo, October 2012.

Future Challenges



- Generative Biophysical Models of Atrophy
 - Based on Discovered atrophy regions
 - From geometry & Statistics to biological and physical laws
- Synthetic but Realistic Databases of multimodal images with ground truth
 - for training and benchmarking



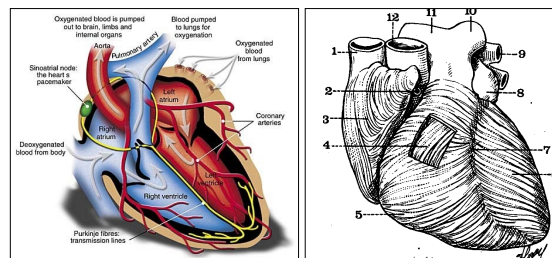
M Lorenzi, N Ayache, X Pennec G B. Frisoni, for ADNI. Disentangling the normal aging from the pathological Alzheimer's disease progression on structural MR images. 5th Clinical Trials in Alzheimer's Disease (CTAD'12), Monte Carlo, October 2012.

3 Clinical Applications



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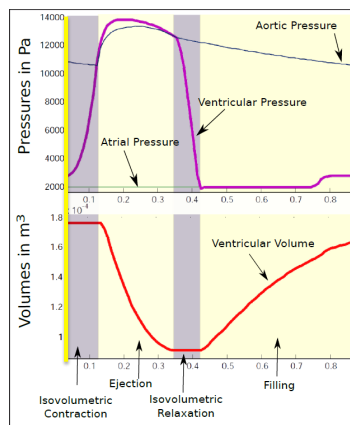
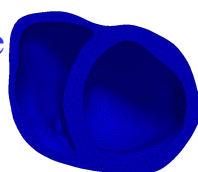
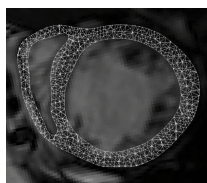
Cardiovascular Diseases



First cause of death in the world
30% of deaths, 17.3 millions in 2008 (WHO)

Computational Cardiac Model

- to Integrate
 - imaging & electrical & hemodynamic & biological measures
- to Quantify & Simulate cardiac function

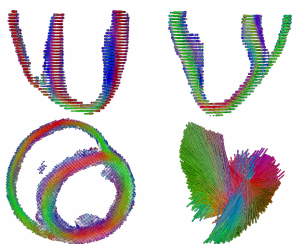


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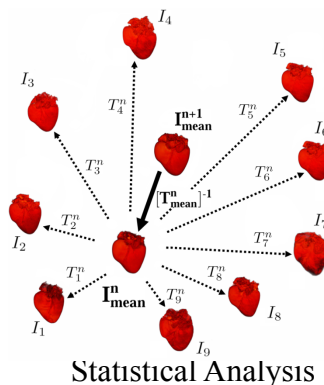
From Biomedical Images to Virtual
Personalized Physiological Patients

1. Anatomy & Structure

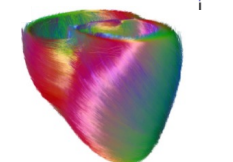
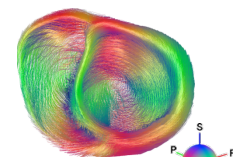
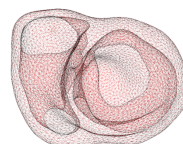
- Cardiac Atlas (NIH & Creatis)



DTI Images



Statistical Analysis



Average structure

H Lombaert, JM Peyrat, P Croisille, S Rapacchi, L Fanton, P Clarysse, H Delingette, N Ayache. Statistical Analysis of the Human Cardiac Fiber Architecture from DT-MRI. FIMH 2011

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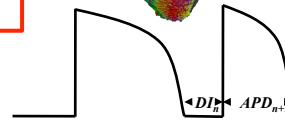
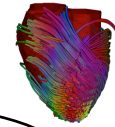
2. Electrophysiology: Mitchell-Schaeffer Model

Simplified from Fenton- Karma

Phenomenological model of Sodium (Na^+), Calcium (Ca^{2+}) & Potassium (K^+) currents.

$$\begin{cases} \partial_t u = \text{div}(d_{MS} M \nabla u) + \frac{zu^2(1-u)}{\tau_{in}} - \frac{u}{\tau_{out}} + J_{stim}(t) \\ \partial_t z = \begin{cases} \frac{(1-z)}{\tau_{open}} & \text{if } u < u_{gate} \\ \frac{-z}{\tau_{close}} & \text{if } u > u_{gate} \end{cases} \end{cases}$$

Matrix M : cardiac fibers

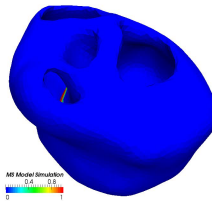


Variables :

u cardiac action potential
 z Na^+ & Ca^{2+} gate potential

Parameters :

d_{MS} Diffusion coefficient
 τ_{in} Na^+ & Ca^{2+} currents time-constant
 τ_{out} K^+ current -
 τ_{open} Na^+ & Ca^{2+} gate opening -
 τ_{close} Na^+ & Ca^{2+} gate closing -



All Model Simulation
 0 0.4 0.8

[MS03] C. Mitchell and D. Schaeffer, "A two-current model for the dynamics of cardiac membrane,"
 Bulletin of mathematical biology, vol. 65, no. 5, pp. 767-793, 2003.

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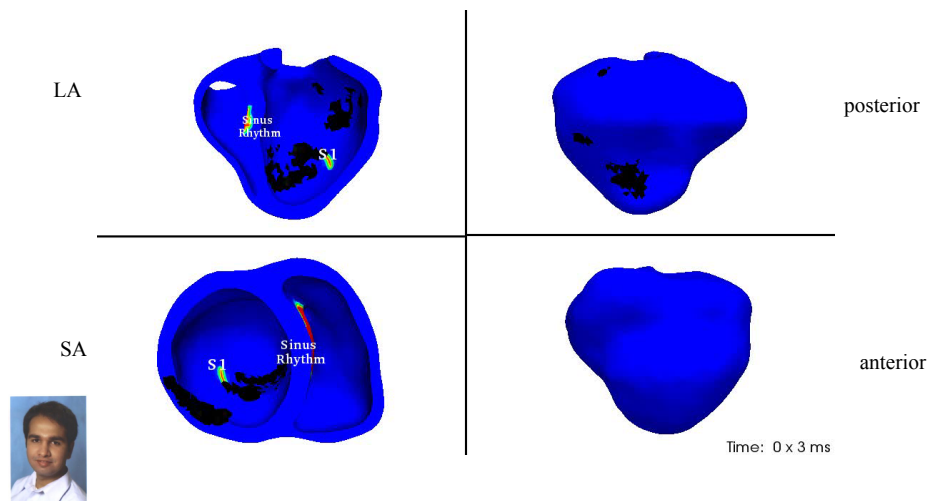
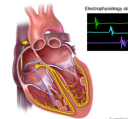
- Decoupling of c and APD
- APD as a function of diastolic interval DI (Restitution curve)

informatics mathematics
 Inria

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Predict Ventricular Tachycardia

- VT-stim Protocol simulated near scars at high frequencies (S1 - 400ms, 150bpm)

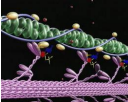


J. Relan, P. Chinchapatnam, M. Sermesant, K. Rhode, M. Ginks, H. Delingette, C. A. Rinaldi, R. Razavi, N. Ayache., "Coupled personalisation of cardiac electrophysiology models for prediction of ischemic ventricular tachycardia," *Royal Society Journal on Interface Focus*, (3):396-407, 2011.



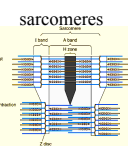
3. Mechanical Model

ATP



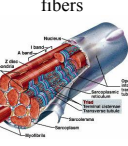
nano

sarcomeres



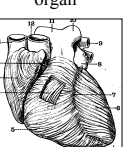
micro

fibers



méso

organ



macro

Inspired by Hill-Maxwell rheological model

M. Sorine

active **non-linear viscoelastic anisotropic incompressible** material.

$$\rho \ddot{P} - \text{div}(K_p \varepsilon_p + C_p \dot{\varepsilon}_p + \sigma_c + C_c \dot{\varepsilon}_c + K_c \xi_0) = 0$$

$$\partial_t K_c = K_0 |u|_+ - (|\dot{\varepsilon}_c| + |u|) K_c$$

$$\partial_t \sigma_c = \sigma_0 |u|_+ - (|\dot{\varepsilon}_c| + |u|) \sigma_c + K_c \dot{\varepsilon}_c$$

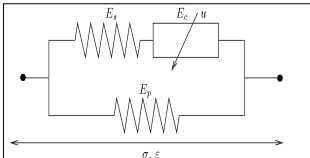
$$\sigma_c + C_c \dot{\varepsilon}_c + K_c \xi_0 = K_s (\varepsilon_p - \varepsilon_c)$$

K_c stiffness


u action potential

ε_c strain

σ_c stress



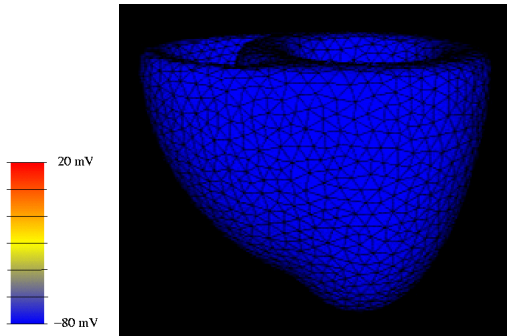
E_s and E_p : elastic material laws,
 E_c contractile electrically-activated element.



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J. Bestel, F. Clément, and M. Sorine. *A Biomechanical Model of Muscle Contraction* MICCAI 2001.
 D. Chapelle, P. Le Tallec, P. Moireau, M. Sorine. *An energy-preserving muscle tissue model: formulation and compatible discretizations*, International Journal of Multiscale Computational Engineering, 2010

Electro-Mechanical Simulation



• Action potential u controls contractile element:

- $u > 0$: Contraction
- $u \leq 0$: Relaxation

• u also modifies stiffness k of the material.

action potential u



M. Sermesant, H. Delingette, N. Ayache. An Electromechanical Model of the Heart for Image Analysis and Simulation. *IEEE Transactions on Medical Imaging*. 2006 May;25(5):612-25.

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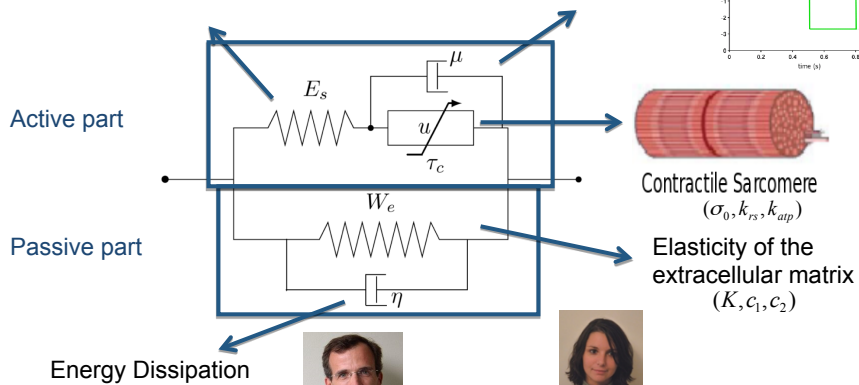
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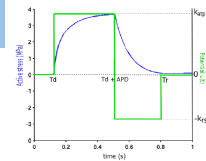
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Parameters of Bestel-Clement-Sorine model

→10 global parameters to estimate



Stéphanie Marchesseau



Marchesseau, MICCAI 2012

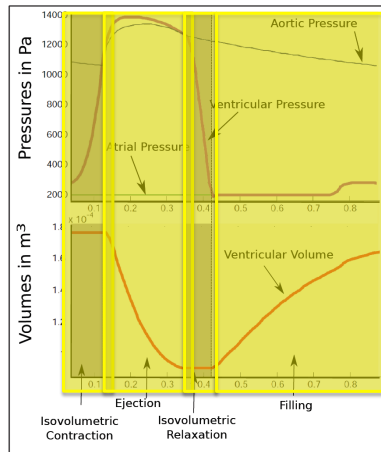


[Bestel .et al, 2001] [Chapelle et al, 2012]

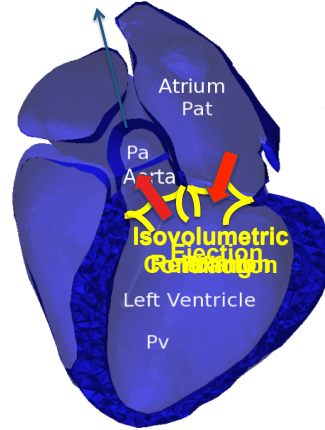
Rennes 9 Nov. 2012 - 26

Parameters of Windkessel Model

→ 4 additional global parameters to estimate



4-element Windkessel
(R_p, C, Z_c, L)



Marchesseau, MICCAI 2012



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Methods for Mechanical Personalization

- Variational



H. Delingette

- Adjunct method to compute functional gradient

H. Delingette, F. Billet, K. C. L. Wong, M. Sermesant, K. Rhode, M. Ginks, C. A. Rinaldi, R. Razavi, and N. Ayache. Personalization of Cardiac Motion and Contractility from Images using Variational Data Assimilation. IEEE Trans. in Biomedical Engineering Letters, 2011.

- Optimal Filtering



D. Chapelle

- Unscented Kalman Filter to jointly estimate state variables and model parameters (recursive)

A. Imperiale, R. Chabiniok, P. Moireau, and D. Chapelle, Constitutive Parameter Estimation Methodology Using Tagged-MRI Data, FIMH 2011

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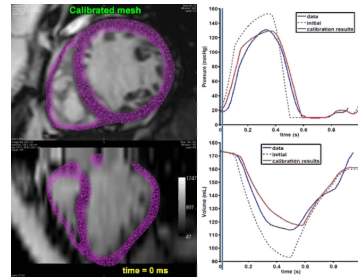
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Diagnostic Value?

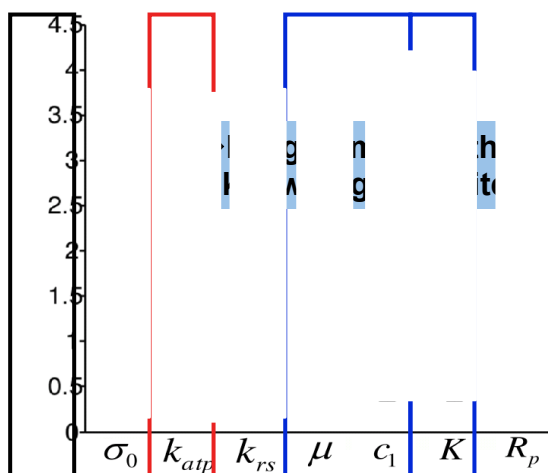
- First Specificity Study
 - 7 Physiological Parameters
 - 6 Healthy Controls
 - 2 HF Patients
 - 1 Dilated Cardio-Myopathy (DCM)
 - 1 post-Myocardial Infarction (post-MI)



S. Marchesseau, H. Delingette, M. Sermesant, K. Rhode, S.G. Duckett, C.A. Rinaldi, R. Razavi, & N. Ayache. Cardiac Mechanical Parameter Calibration based on the Unscented Transform. In MICCAI 2012

Preliminary Specificity Study

DCM HF ▲ Post-MI HF ● Healthy □



→ DCM HF has higher stiffness (c_1 and K)

→ DCM HF has smaller oh resistance (R_p)

Post-MI HF has smaller relaxation rate (k_{rs})

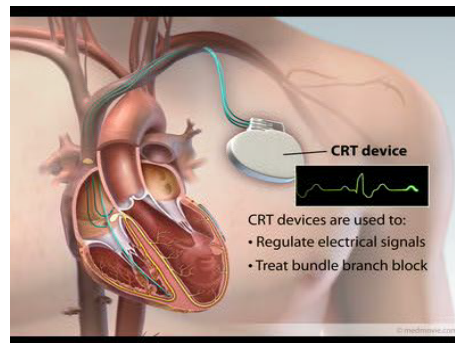
→ Both HF groups have similar conductivity (μ) as healthy controls

Pathological cases

S. Marchesseau, H. Delingette, M. Sermesant, K. Rhode, S.G. Duckett, C.A. Rinaldi, R. Razavi, & N. Ayache. Cardiac Mechanical Parameter Calibration based on the Unscented Transform. In MICCAI 2012

Predictive Value?

- Predict the effect of a Cardiac Resynchronization Therapy (CRT)



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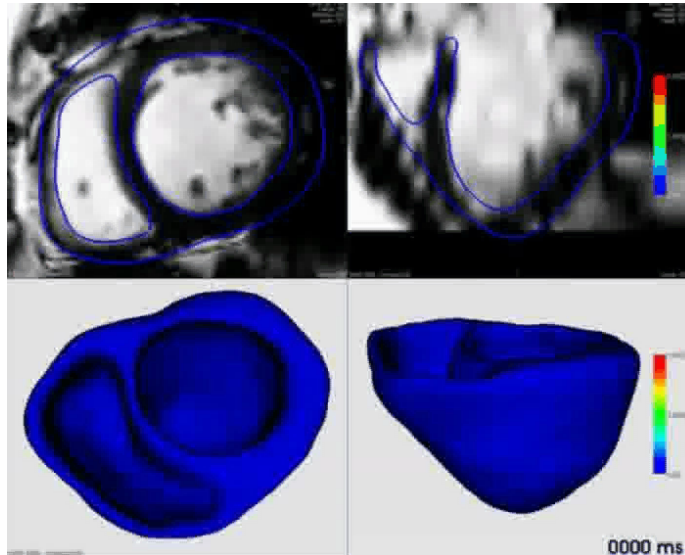
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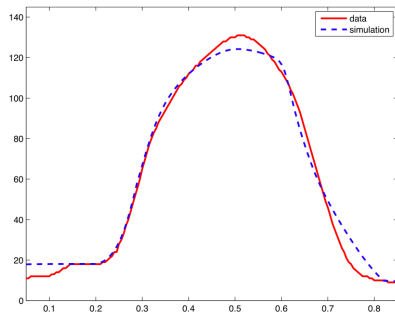
Personalized Asynchronous Heart

Woman
60 years
LBBB
asynchrony

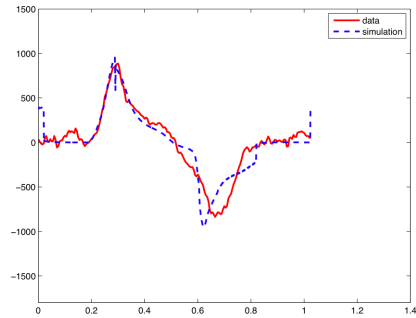


M. Sermesant, F. Billet, R Chabiniok, T Mansi, P Chinchapatnam, P Moireau, JM Peyrat, K Rhode, M Ginks, P Lambiase, S Arridge, H Delingette, M Sorine, A Rinaldi, D Chapelle, R Razavi, N Ayache, *Personalised Electromechanical Model of the Heart for the Prediction of the Acute Effects of Cardiac Resynchronisation Therapy*, Medical Image Analysis 2012

Pressure and dP/dt Curves



Measured (solid red) and simulated (dashed blue) **pressure** curves in sinus rhythm.

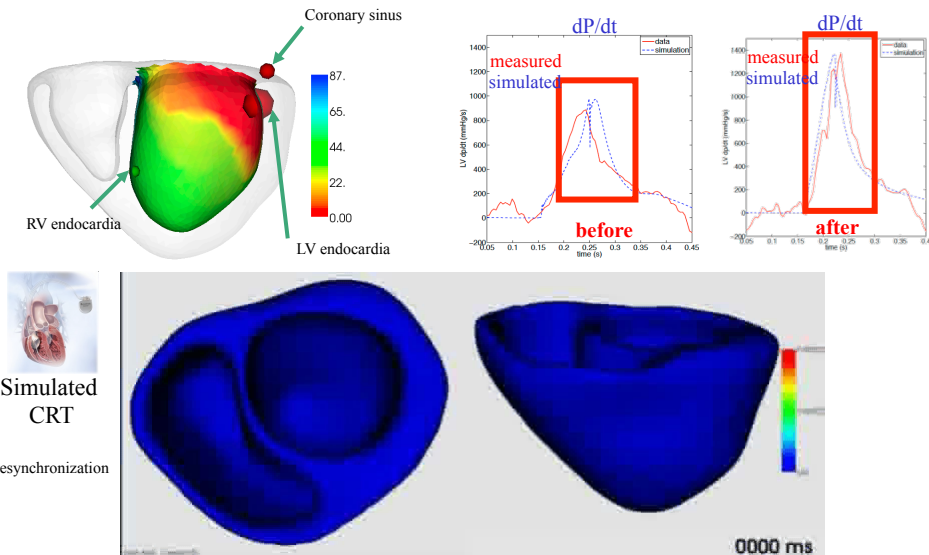


Measured (solid red) and simulated (dashed blue) **dP/dt** curves in sinus rhythm.

Personalised electromechanical model reproduces pressure characteristics

M. Sermesant, F. Billet, R Chabiniok, T Mansi, P Chinchapatnam, P Moireau, JM Peyrat, K Rhode, M Ginks, P Lambiase, S Arridge, H Delingette, M Sorine, A Rinaldi, D Chapelle, R Razavi, N Ayache, *Personalised Electromechanical Model of the Heart for the Prediction of the Acute Effects of Cardiac Resynchronisation Therapy*, *Medical Image Analysis* 2012

Virtual Pacemaker



M. Sermesant, F. Billet, R Chabiniok, T Mansi, P Chinchapatnam, P Moireau, JM Peyrat, K Rhode, M Ginks, P Lambiase, S Arridge, H Delingette, M Sorine, A Rinaldi, D Chapelle, R Razavi, N Ayache, *Personalised Electromechanical Model of the Heart for the Prediction of the Acute Effects of Cardiac Resynchronisation Therapy*, *Medical Image Analysis* 2012

Validated dP/dT for 2 patients for various positions of the leads

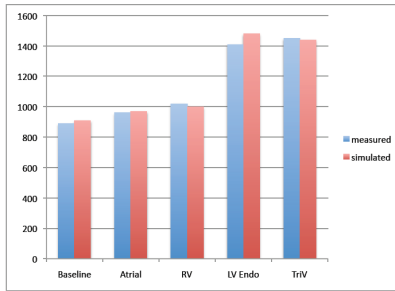


Figure 16: Patient 1: Measured (blue) and simulated (red) $(dP/dt)_{max}$ for different pacing conditions. Parameters were estimated on baseline and then kept constant.

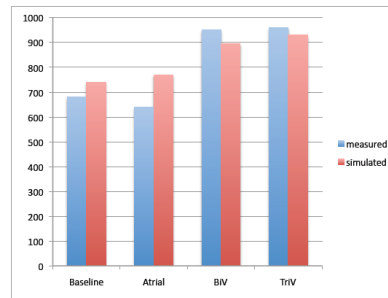


Figure 17: Patient 2: Measured (blue) and simulated (red) $(dP/dt)_{max}$ for different pacing conditions. Parameters were estimated on baseline and then kept constants.

M. Sermesant, F. Billet, R Chabiniok, T Mansi, P Chinchapatnam, P Moireau, JM Peyrat, K Rhode, M Ginks, P Lambiase, S Arridge, H Delingette, M Sorine, A Rinaldi, D Chapelle, R Razavi, N Ayache, *Personalised Electromechanical Model of the Heart for the Prediction of the Acute Effects of Cardiac Resynchronisation Therapy*, *Medical Image Analysis* 2012

What Else?



Image Simulation

- Vary parameters of Biophysical Model to generate databases of realistic images with ground truth



- To benchmark Image Processing Algorithms
- To Train Machine Learning Algorithms

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Personalized Physiological Patients




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Real vs. Synthetic MRI



<p>Image 001_111114 Voxel size: 1.42x0.14x0.01 X: 132.26 mm Y: 125.51 mm WW/WL: 129 / 653</p>	<p>Real MRI</p> <p>No model Unknown Motion</p>	
<p>Image 001_111114 Voxel size: 1.42x0.14x0.01 X: 132.26 mm Y: 125.51 mm WW/WL: 129 / 653</p>	<p>Synthetic MRI</p> <p>Known Motion + Model Parameters</p>	

 A Prakosa, M Sermesant, H Delingette, S Marchesseau, E Saloux, P Allain, N Villain, and N Ayache. Generation of Synthetic but Visually Realistic Time Series of Cardiac Images Combining a Biophysical Model and Clinical Images. IEEE Transactions on Medical Imaging, 2012. In press.

Real vs. Synthetic MRI



Real MRI
No model
Unknown Motion

Synthetic MRI
Known Motion
+ Model Parameters

image alignment

A Prakosa, M Sermesant, H Delingette, S Marchesseau, E Saloux, P Allain, N Villain, and N Ayache. Generation of Synthetic but Visually Realistic Time Series of Cardiac Images Combining a Biophysical Model and Clinical Images. IEEE Transactions on Medical Imaging, 2012. In press.

Machine Learning for EP

- Preliminary promising results for EP:
 - Depolarisation Times (DT) learned from strain measurements on simulated images



A Prakosa, M Sermesant, H Delingette, S. Marechesseau, N Ayache. Cardiac Electro-physiological Activity Pattern Learning from Synthetic Images; Submitted 2012. Earlier version in MICCAI 2011

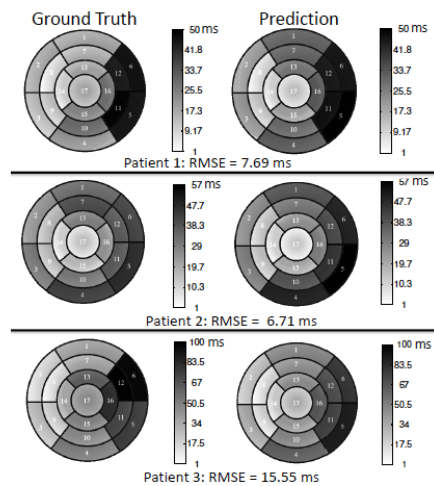


Fig. 4. Depolarization Time Estimation from Clinical 3D MR Sequences. First evaluation of the learning process in the prediction of the LV surface depolarization time on a patient (left) is compared to the ground truth value. Similar pattern in the same range is observed on both of them.

Virtual Physiological Patient & Computational Biomedical Imaging

Opens new frontiers towards

- A paradigm shift from
 - reactive standardized medicine
- Towards
 - preventive predictive personalized



Medicine of 21st century.

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Thank You!



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