



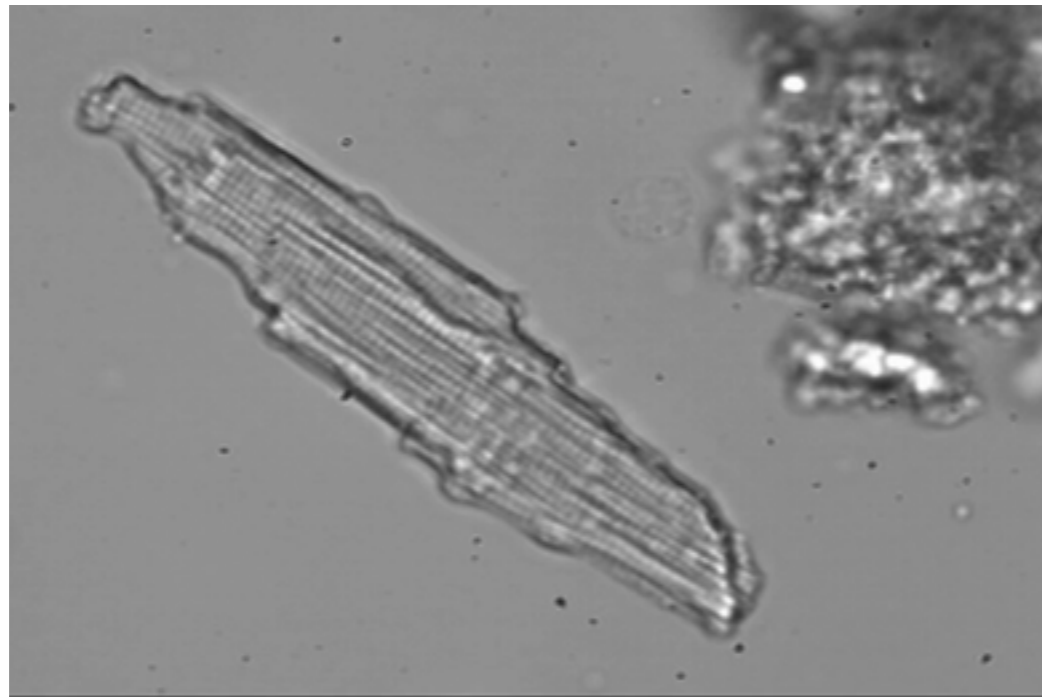
***Biomechanical modeling of the heart:  
From multi-scale multi-physics formulations to  
patient-specific simulations, with experimental  
validations and clinical applications***

**D. Chapelle**, with P. Moireau, M. Caruel, R. Chabiniok...  
Inria Saclay-Ile-de-France, M $\Xi$ DISIM team

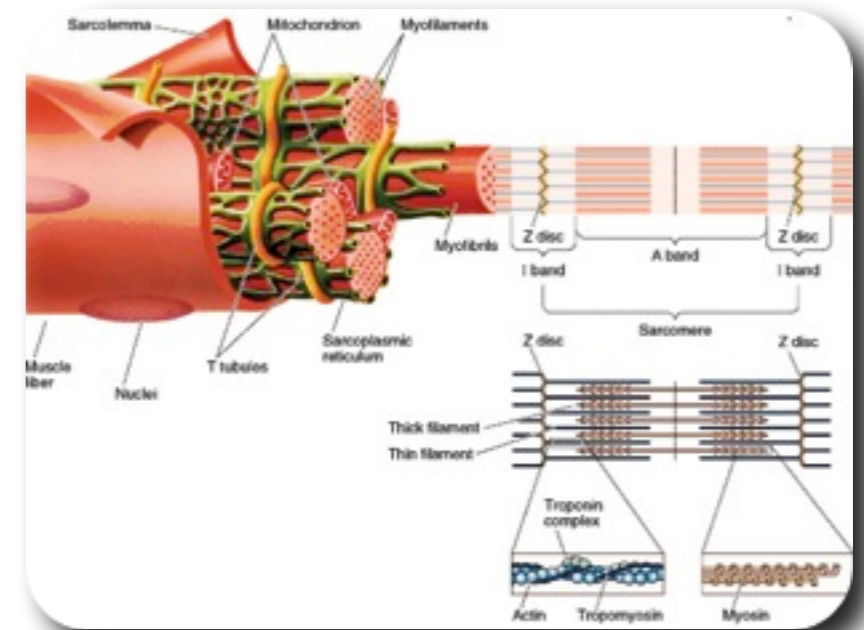
# Outline

- Multiscale modeling of the myocardium  
Focus on *mechanical* behavior, with chemical / electrical input
- Validation against *experimental* data (papillary muscles)
- Modeling and validation at the organ scale:  
→ Illustration with CRT simulations
- Specific considerations on *estimation* for patient-specific modeling:  
→ Detailed validation with infarct characterization
- Conclusions

# Multiscale heart modeling: (I) Micro



Courtesy: R. Peyronnet (Imperial)



# Multiscale heart modeling: (I) Micro

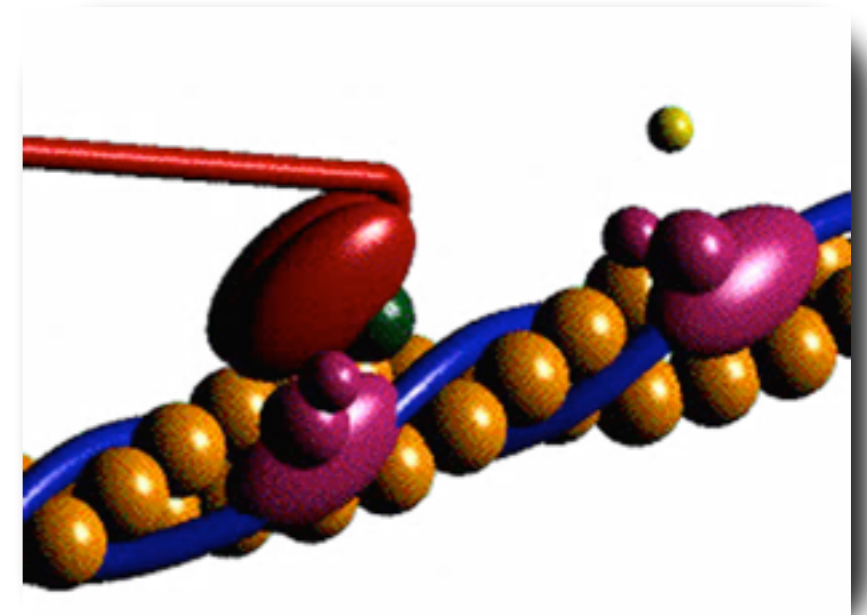
- **Actin-Myosin bridges:** Huxley 57 revisited

$$\frac{\partial n}{\partial t} + \dot{e}_c \frac{\partial n}{\partial s} = (n_0 - n)f - ng$$

$n(s,t)$  : ratio attached bridges for heads  
at distance  $s$  from actin site / time  $t$

$f / g$  : binding / unbinding rate

$n_0$  : ratio of actually available sites  
(Frank-Starling, perfusion, etc.)



# Multiscale heart modeling: (I) Micro

- **Actin-Myosin bridges:** Huxley 57 revisited

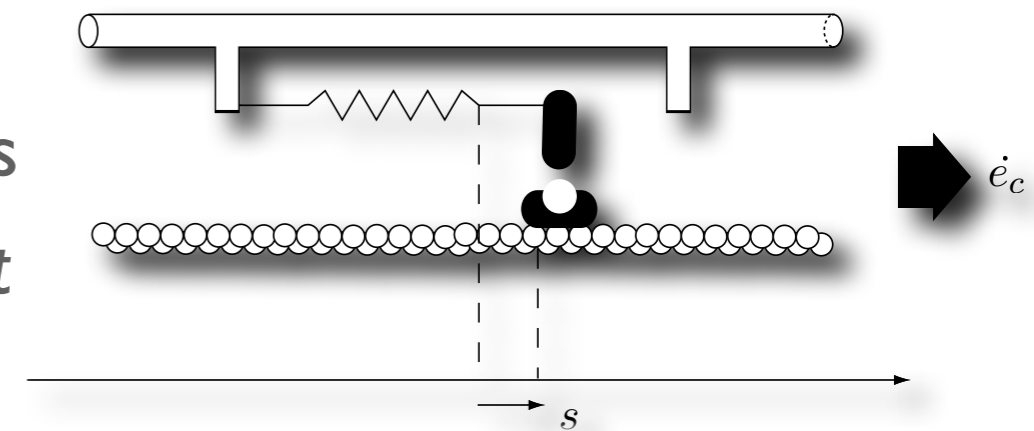
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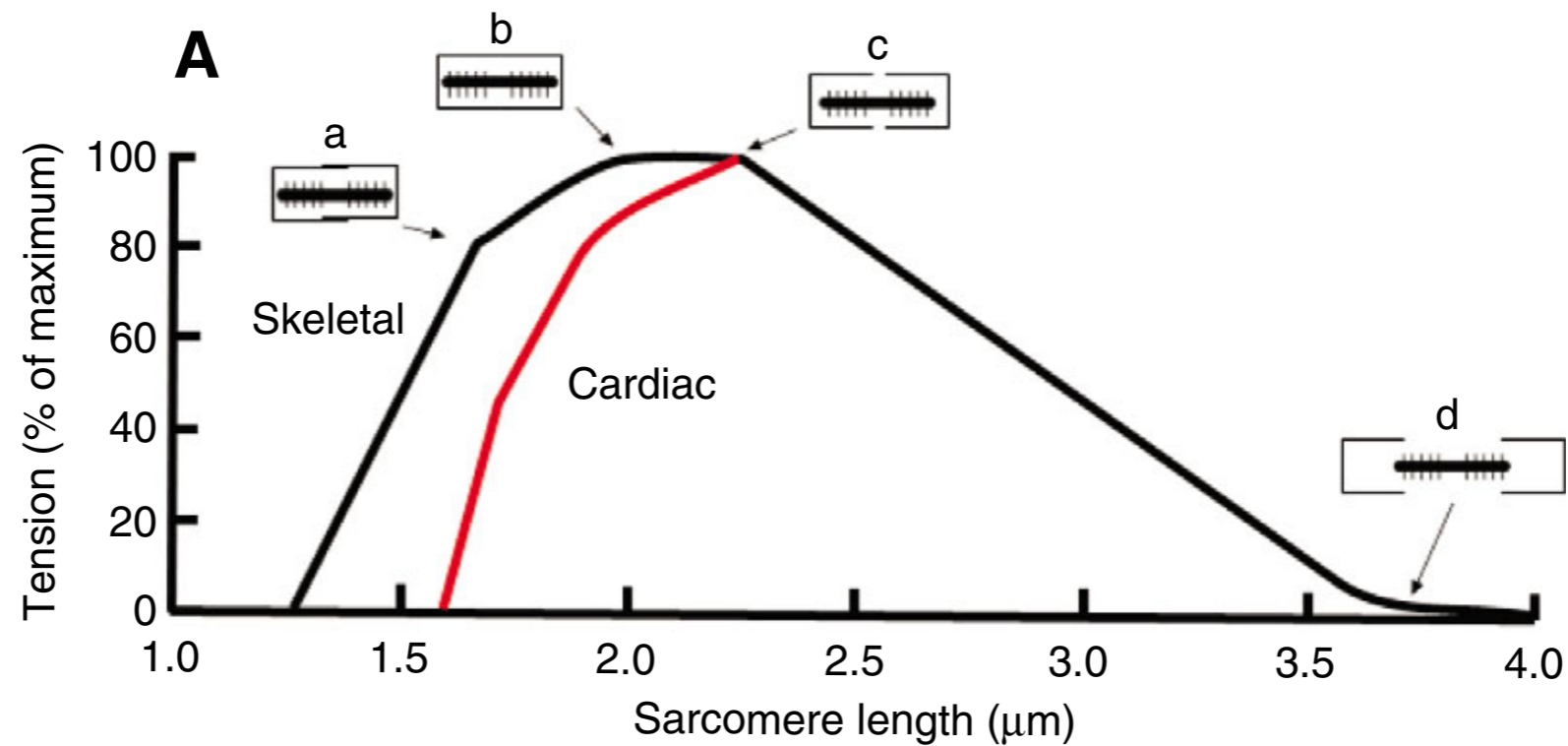
(Frank-Starling, perfusion, etc.)



- To be modeled:  $f(s,t)$ ,  $g(s,t)$ ,  $W_m(s,t)$  (elastic energy of bridge)

- Resulting sarcomere (active) stress:  $\tau_c(t) = \int_s \frac{\partial W_m(t, s)}{\partial s} n(t, s) ds$

# Active force vs. sarcomere length



H.A. Shiels and E.White, Journal of Experimental Biology 211, 2005 (2008).

$\rightarrow n_0(e_c)$

# Multiscale heart modeling: (2) Meso

- **Moment equations:**  $\mu_p = \int_s s^p n(s, t) ds$

$$\dot{\mu}_p = n_0 f_p - (f + g) \mu_p + p \dot{e}_c \mu_{p-1}$$

assuming  $f + g$  independent of  $s$  (see also Guérin et al. [1])

- Modeling choices:

$$f(t, s) = k_{ATP} \mathbb{I}_{s \in [0, 1]} \mathbb{I}_{[Ca^{2+}] > C}$$

$$g(t, s) = \alpha |\dot{e}_c| + k_{ATP} \mathbb{I}_{s \notin [0, 1]} \mathbb{I}_{[Ca^{2+}] > C} + k_{RS} \mathbb{I}_{[Ca^{2+}] < C}$$

$$W_m(t, s) = \frac{k_0}{2} (s + s_0)^2 \quad (\text{Symmetry breaking})$$

- Papers:

✓ Bestel, Clément, Sorine - *LNCS*, vol. 2208, 2001

✓ Chapelle, Le Tallec, Moireau, Sorine - *IJMCE*, 2012

# Multiscale heart modeling: (3) Macro

- **Active constitutive relation for sarcomeres**

$$k_c = k_0 \int_{\mathbb{R}} n(s, t) ds, \quad \tau_c = k_0 \int_{\mathbb{R}} (s + s_0) n(s, t) ds$$

(stiffness) (stress)

$$\begin{cases} \dot{k}_c = -(|u| + \alpha |\dot{e}_c|) k_c + n_0 k_0 |u|_+ \\ \dot{\tau}_c = -(|u| + \alpha |\dot{e}_c|) \tau_c + \dot{e}_c k_c + n_0 \sigma_0 |u|_+ \end{cases}$$

with  $u = k_{ATP} \mathbb{I}_{[Ca^{2+}] > C} - k_{RS} \mathbb{I}_{[Ca^{2+}] < C}$

(action potential related input)

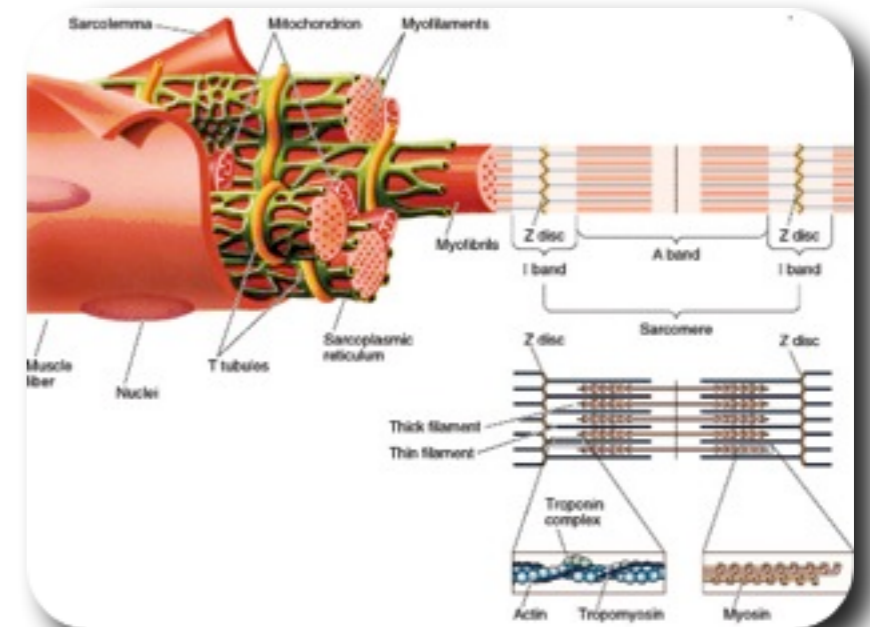
- Microscopic energy  $U_c = \frac{k_0}{2} \int_s (s + s_0)^2 n(s, t) ds$

$$\dot{U}_c = -(|u| + \alpha |\dot{e}_c|) U_c + \dot{e}_c \tau_c + n_0 U_0 |u|_+$$

# Complete rheological modeling

- **Passive components:**

Z-disks, intra- and extra-cellular media, collagen, etc.



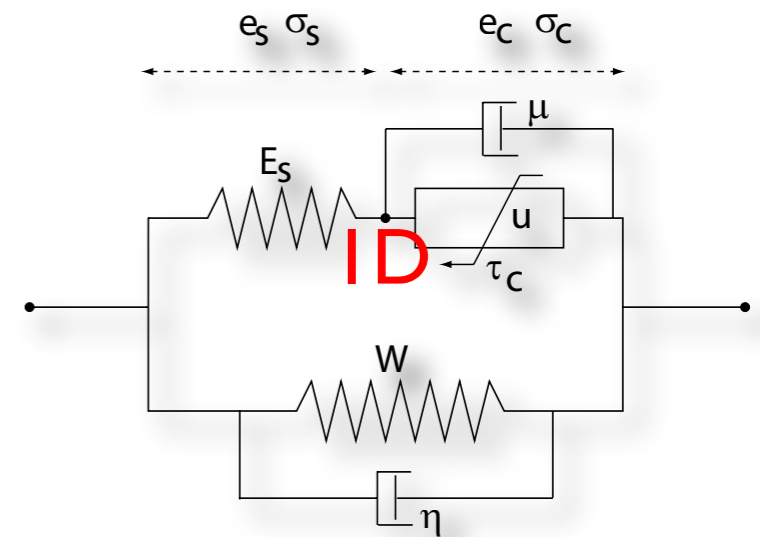
# Complete rheological modeling

- **Passive components:**

Z-disks, intra- and extra-cellular media, collagen, etc.

- Hill-Maxwell rheological model

- Note: sarcomeres generate stresses in *fiber* direction (ID)



- More sophisticated modeling ingredients can be considered in micro-macro approach: addit. chemical states and internal variables...

- Complete energy balance here:

$$\frac{d}{dt} \left( \mathcal{K} + \mathcal{E}_e + \frac{1}{2} \int_{\Omega_0} E_s e_s^2 d\Omega + \int_{\Omega_0} U_c d\Omega \right) =$$

$$\mathcal{P}_{\text{ext}}(\mathbf{v}) + \int_{\Omega_0} n_0 U_0 |u|_+ d\Omega - \int_{\Omega_0} (|u| + \alpha |\dot{e}_c|) U_c d\Omega - \int_{\Omega_0} \mu (\dot{e}_c)^2 d\Omega - \int_{\Omega_0} \frac{\partial W_v}{\partial \dot{\underline{\underline{e}}}} : \dot{\underline{\underline{e}}} d\Omega$$

# ***Myocardium modeling summary***



# Myocardium modeling summary

- Principle of dynamics in total Lagrangian formulation

$$\int_{\Omega_0} \rho \ddot{\underline{y}} \cdot \delta \underline{v} d\Omega_0 + \int_{\Omega_0} \underline{\underline{\Sigma}} : \delta \underline{\underline{e}} d\Omega_0 + \int_{\Gamma} P_V \underline{\nu} \cdot \underline{\underline{F}}^{-1} \cdot \delta \underline{v} J d\Gamma = 0, \quad \forall \delta \underline{v} \in V$$

- Constitutive law

$$\underline{\underline{\Sigma}} = \frac{\partial W^e}{\partial \underline{\underline{e}}} + \frac{\partial W^\eta}{\partial \dot{\underline{\underline{e}}}} + \sigma_{ID}(\underline{e}_{ID}, \underline{e}_c) \underline{n} \otimes \underline{n}$$

✓ Hyperelastic term  $W^e = c_0 e^{c_1(J_1-3)^2} + c_2 e^{c_3(J_4-1)^2} + \kappa[(J-1) - \ln J]$

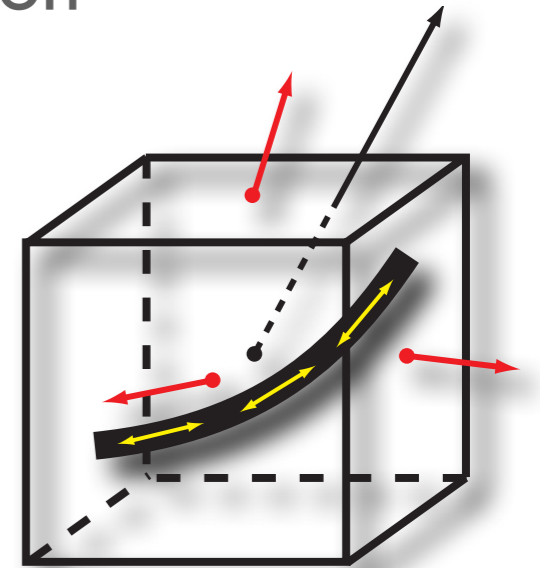
with reduced invariants  $J_1 = (\text{tr} \underline{\underline{C}}) J^{-\frac{2}{3}}, \quad J_4 = (\underline{n} \cdot \underline{\underline{C}} \cdot \underline{n}) J^{-\frac{2}{3}}$

See Prot et al. 07, and also Humphrey&Yin 87, Guccione et al. 91,

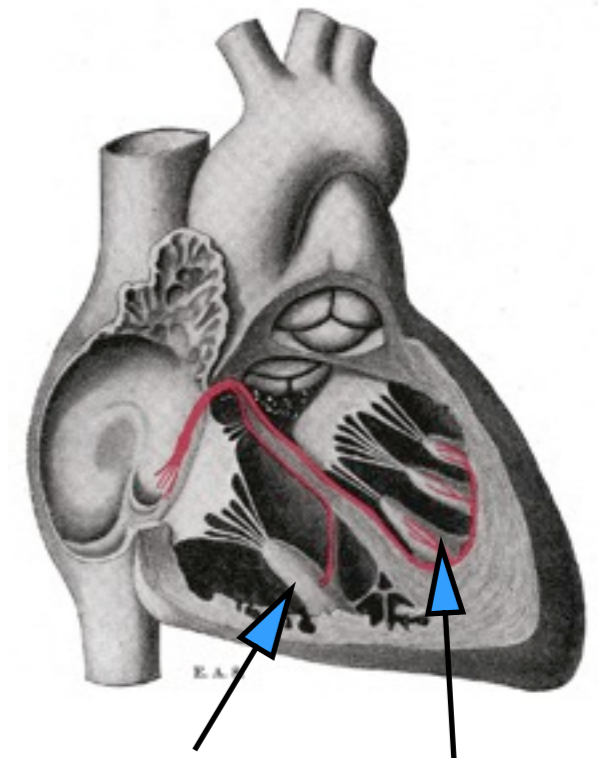
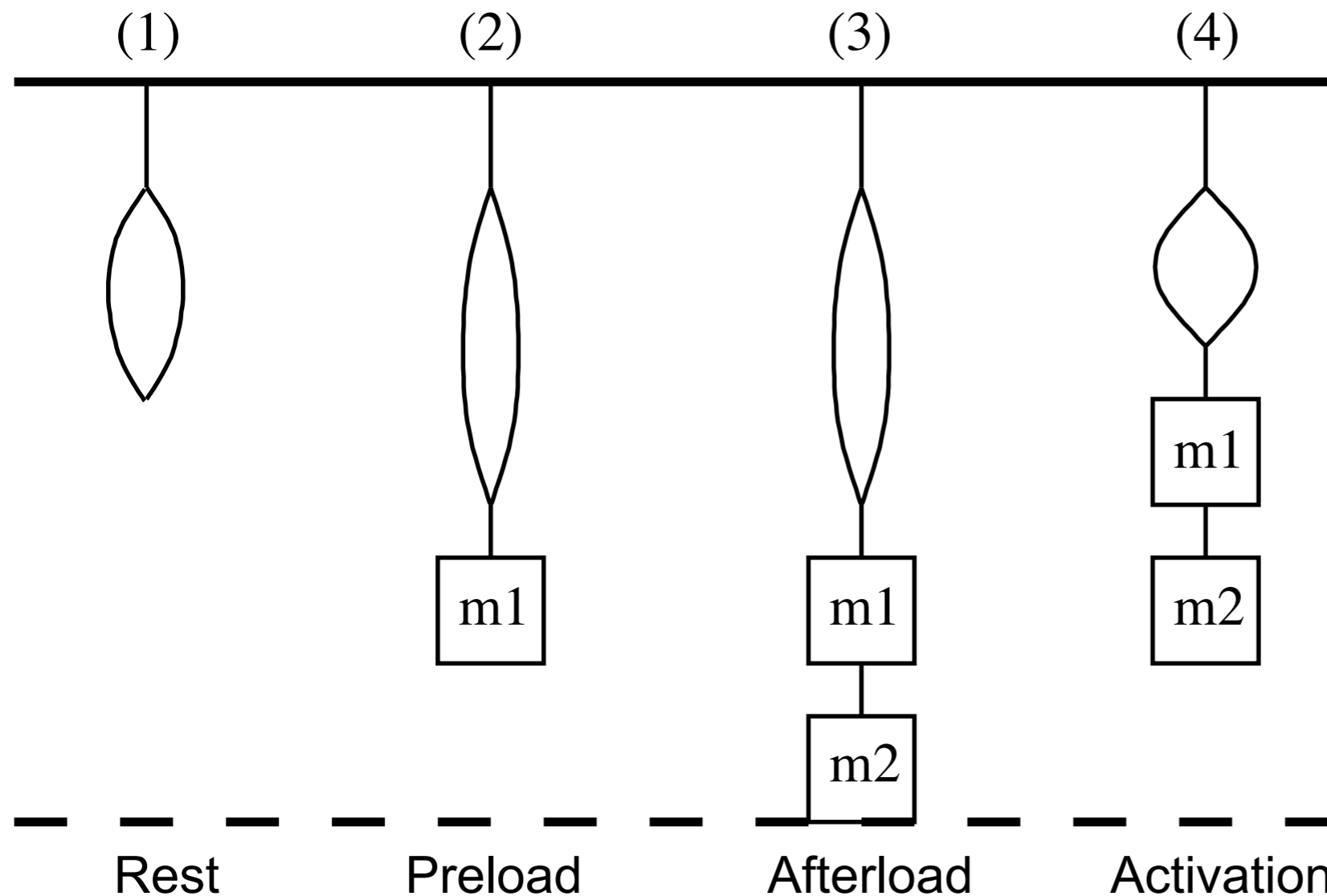
Fung 93, Costa et al. 96, Holzapfel&Ogden 09 (review/analysis)...

✓ Viscous term  $W^\eta = \frac{\eta}{2} \text{tr}(\dot{\underline{\underline{e}}}^2)$

✓ Active part (fiber directed)



# Experimental validation

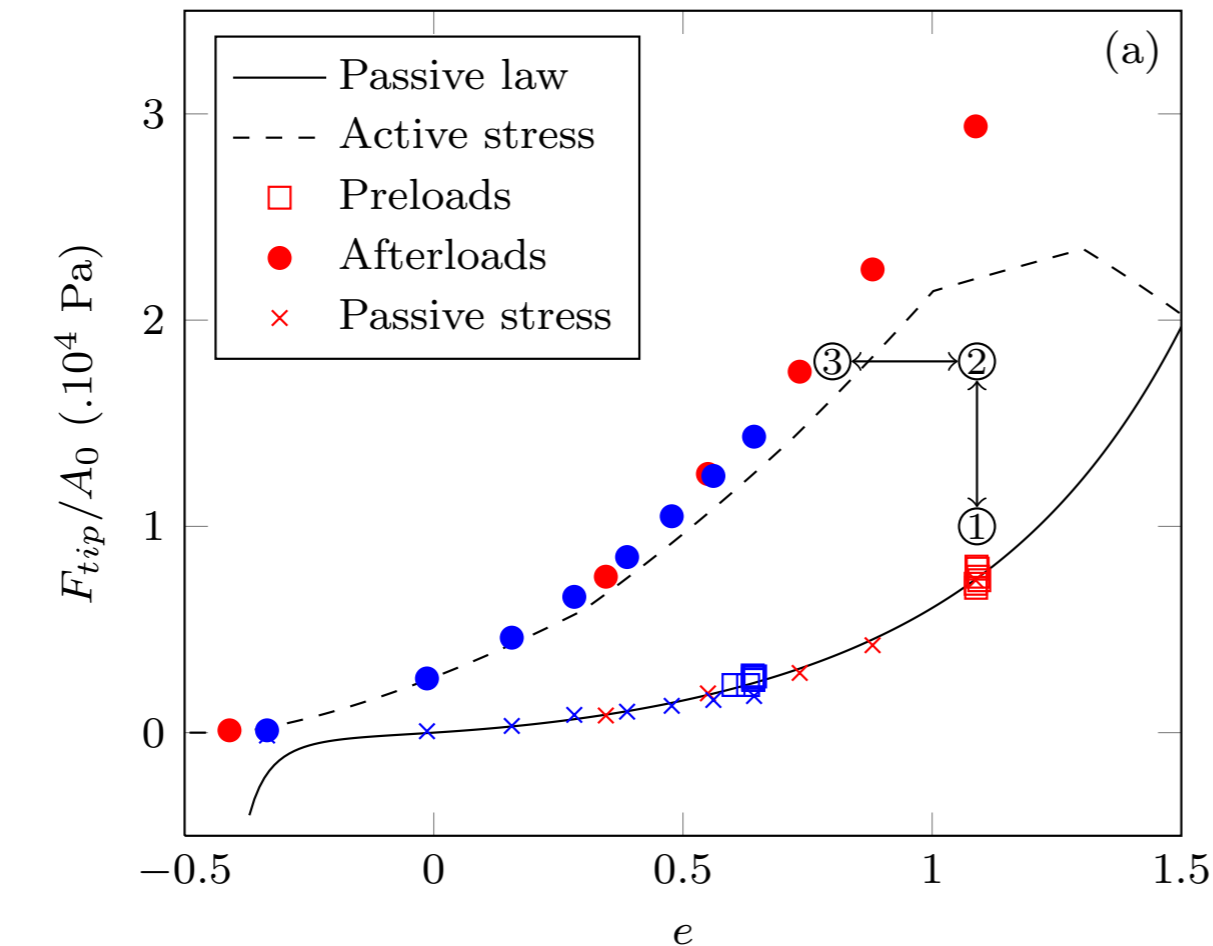


Papillary muscles  
(laboratory rats)

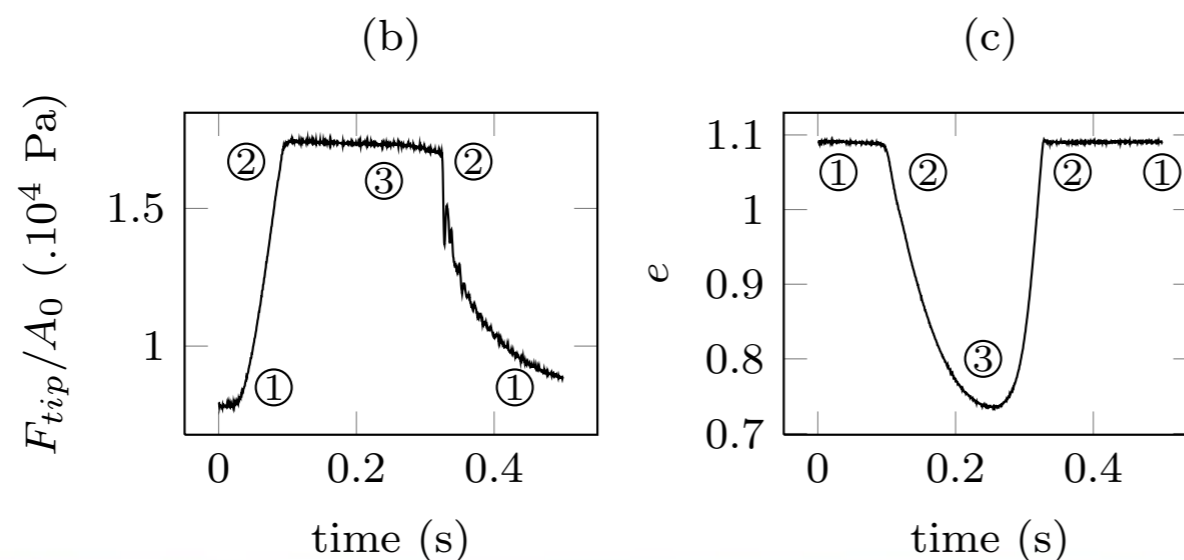
Experimental data : Y. Lecarpentier (Institut du Coeur & Meaux hosp.)

Paper: Caruel, Chabiniok, Moireau, Lecarpentier & Chapelle, *BMMB*'13

# Model vs. experiment: (I) statics

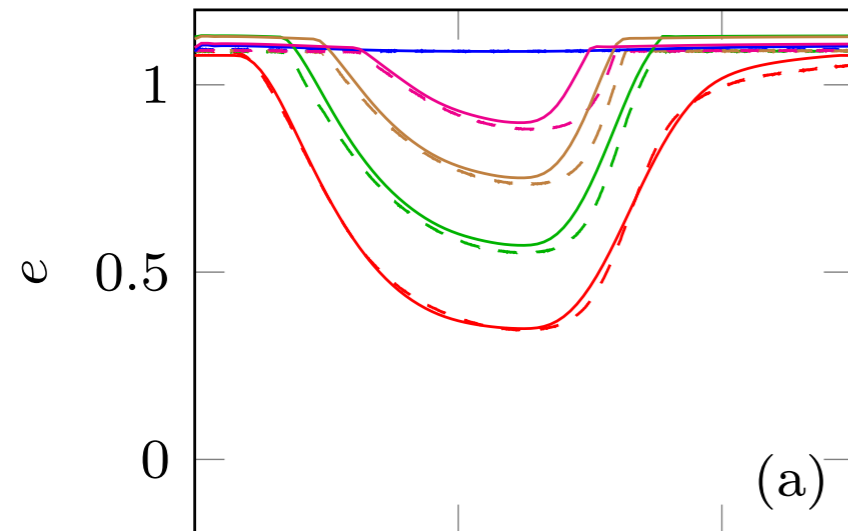


**Stress/strain data  
for initial loading (I)  
and max. shortening (3)**

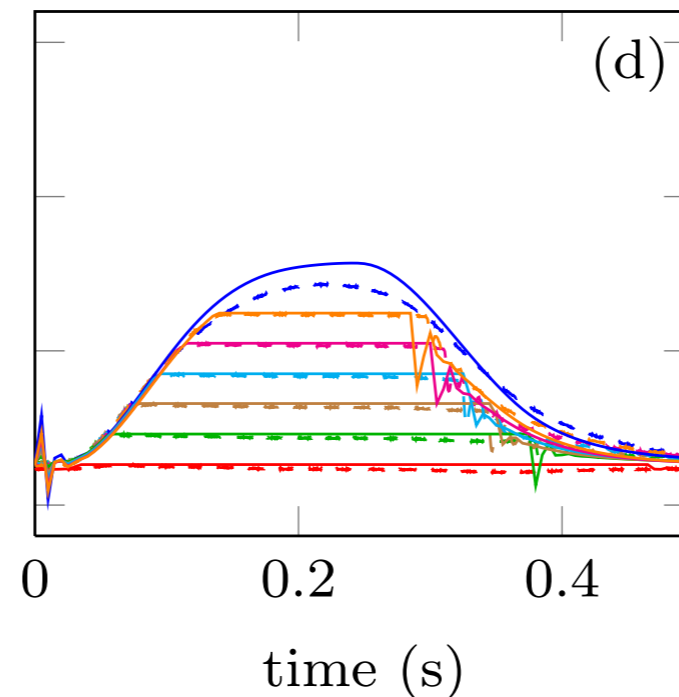
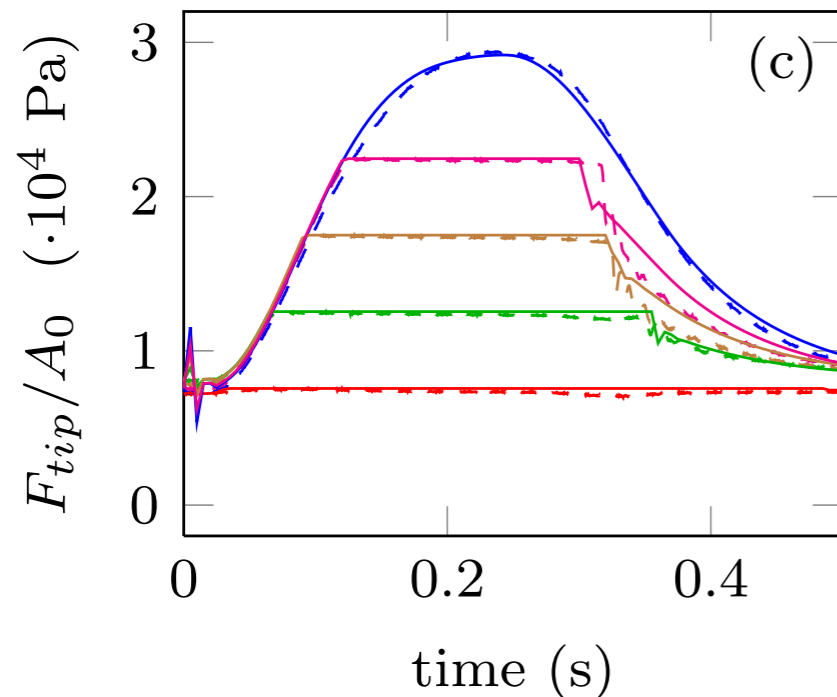
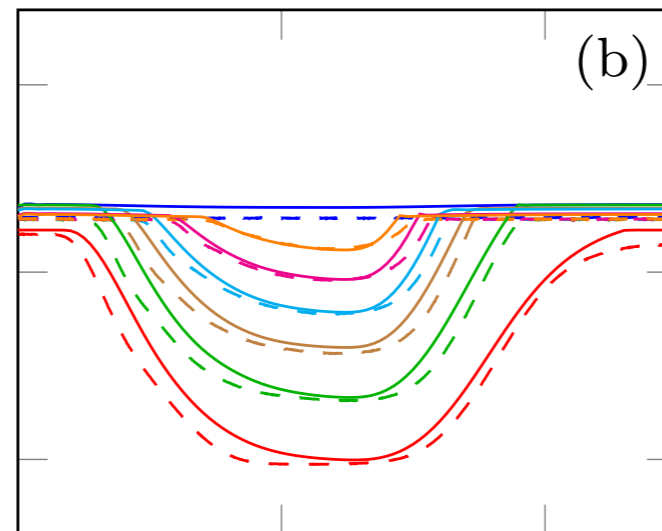


# Model vs. experiment: (2) dynamics

High preload

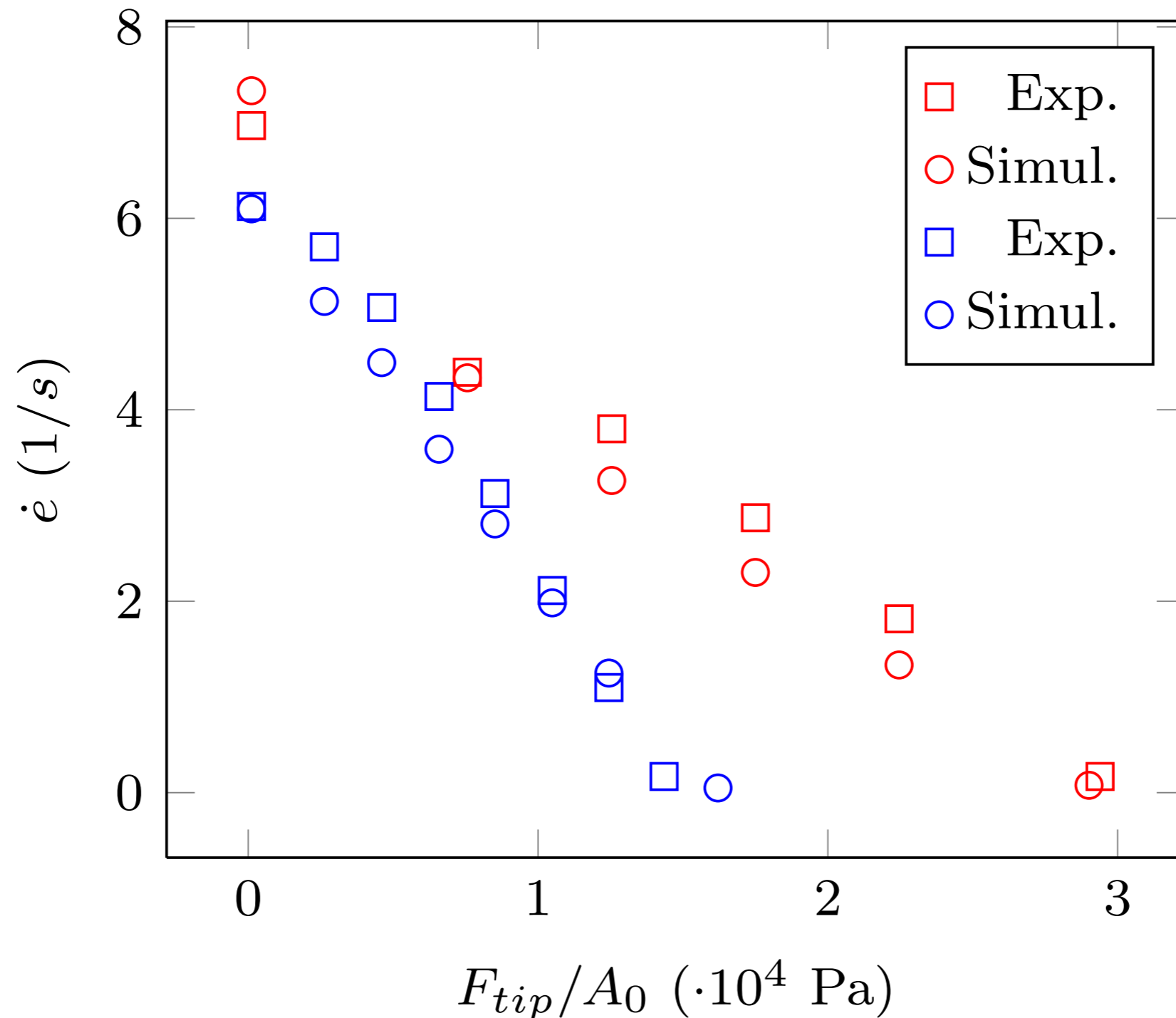


Low preload

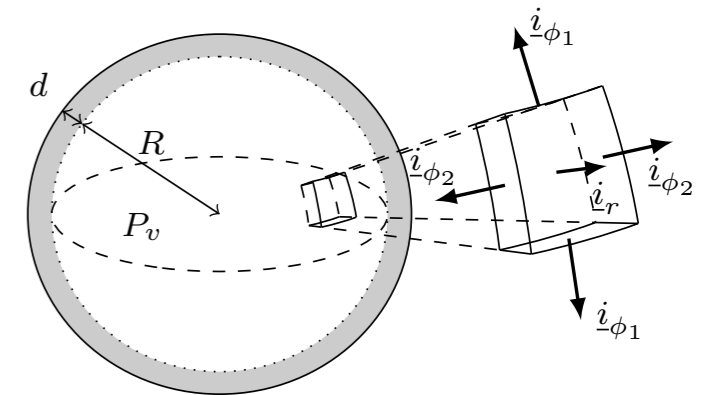
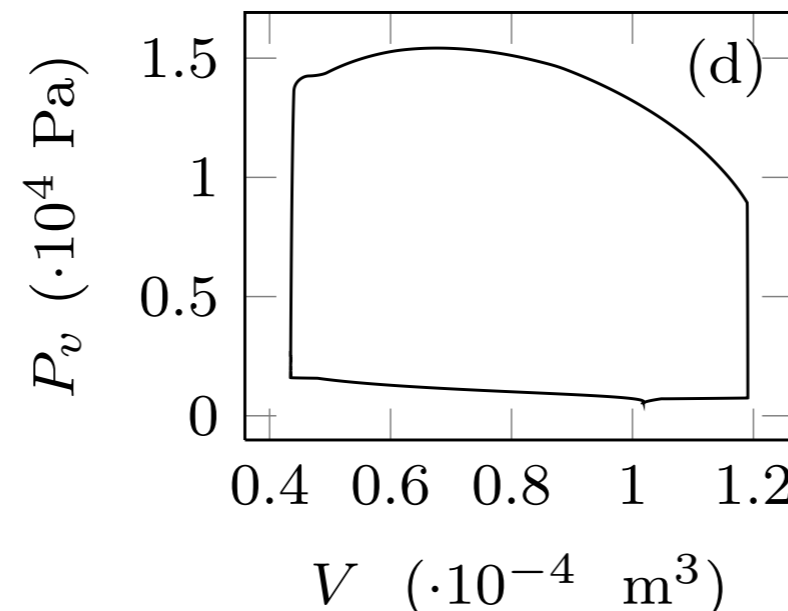
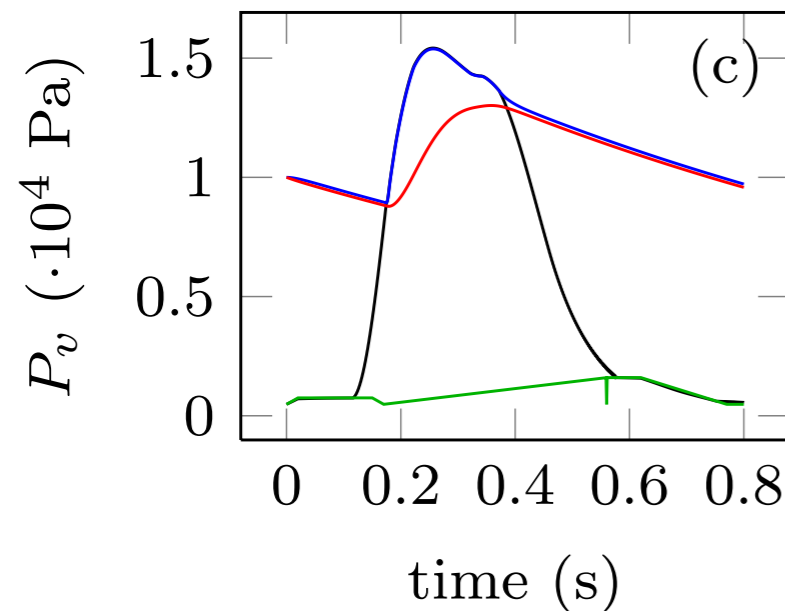
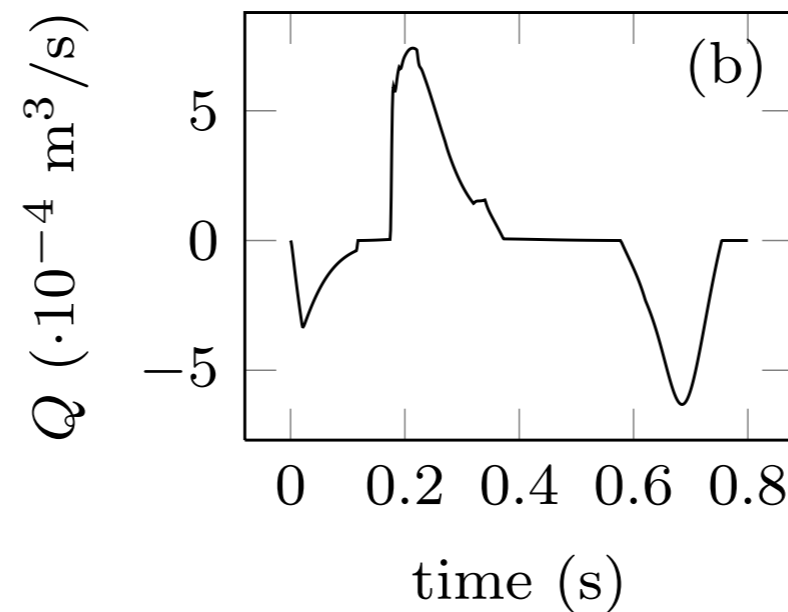
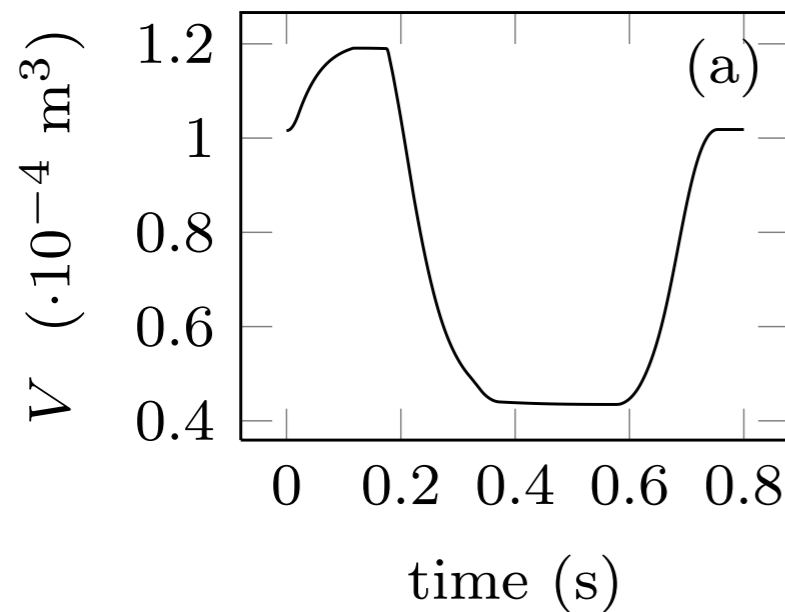


**Dashed / solid lines  
for  
simul. / exp. results**

# Dynamics: Hill's maximum velocity



# Cross-validation with simplified single-cavity heart model

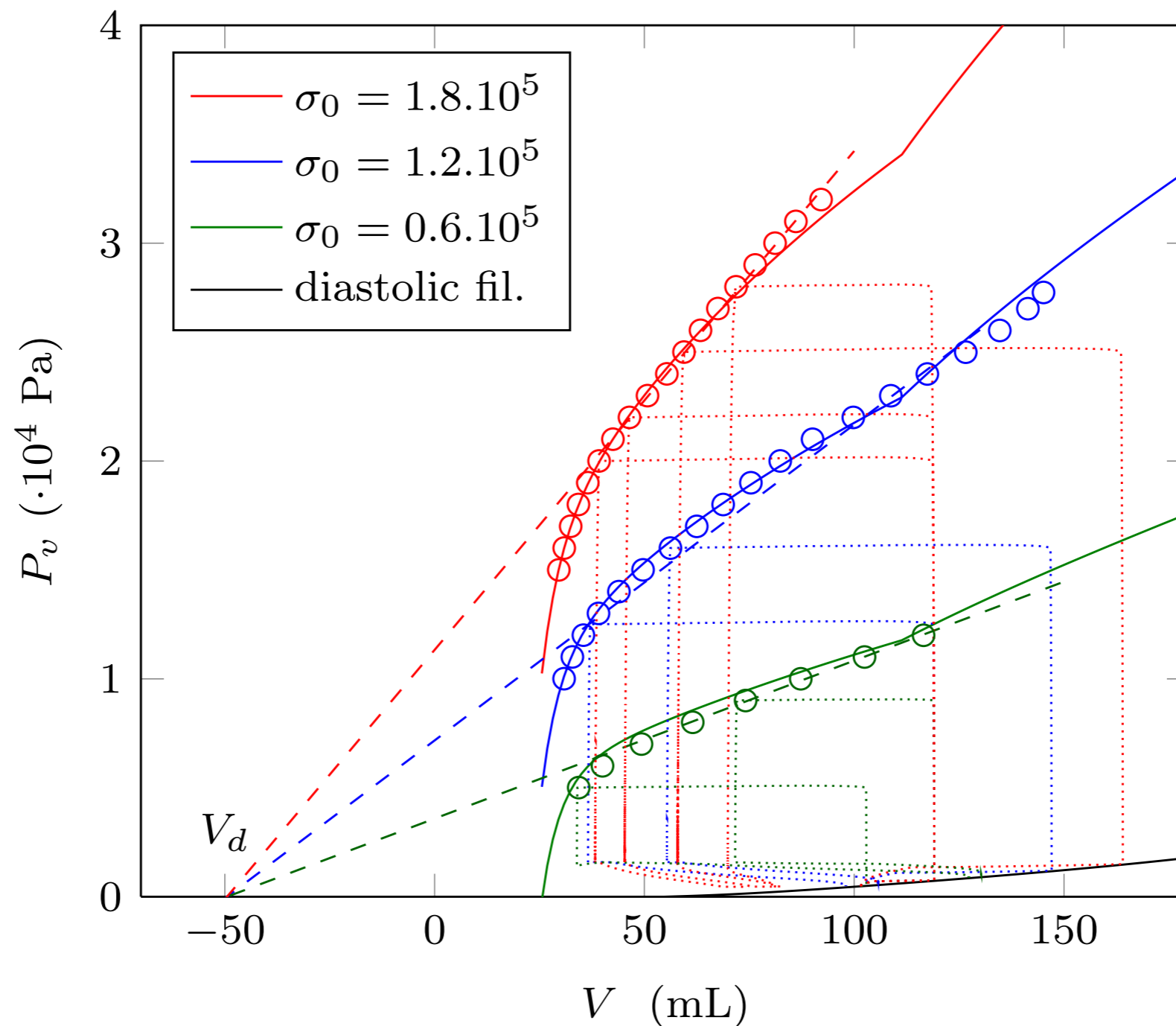


**Simplified spherical symmetry assumption**

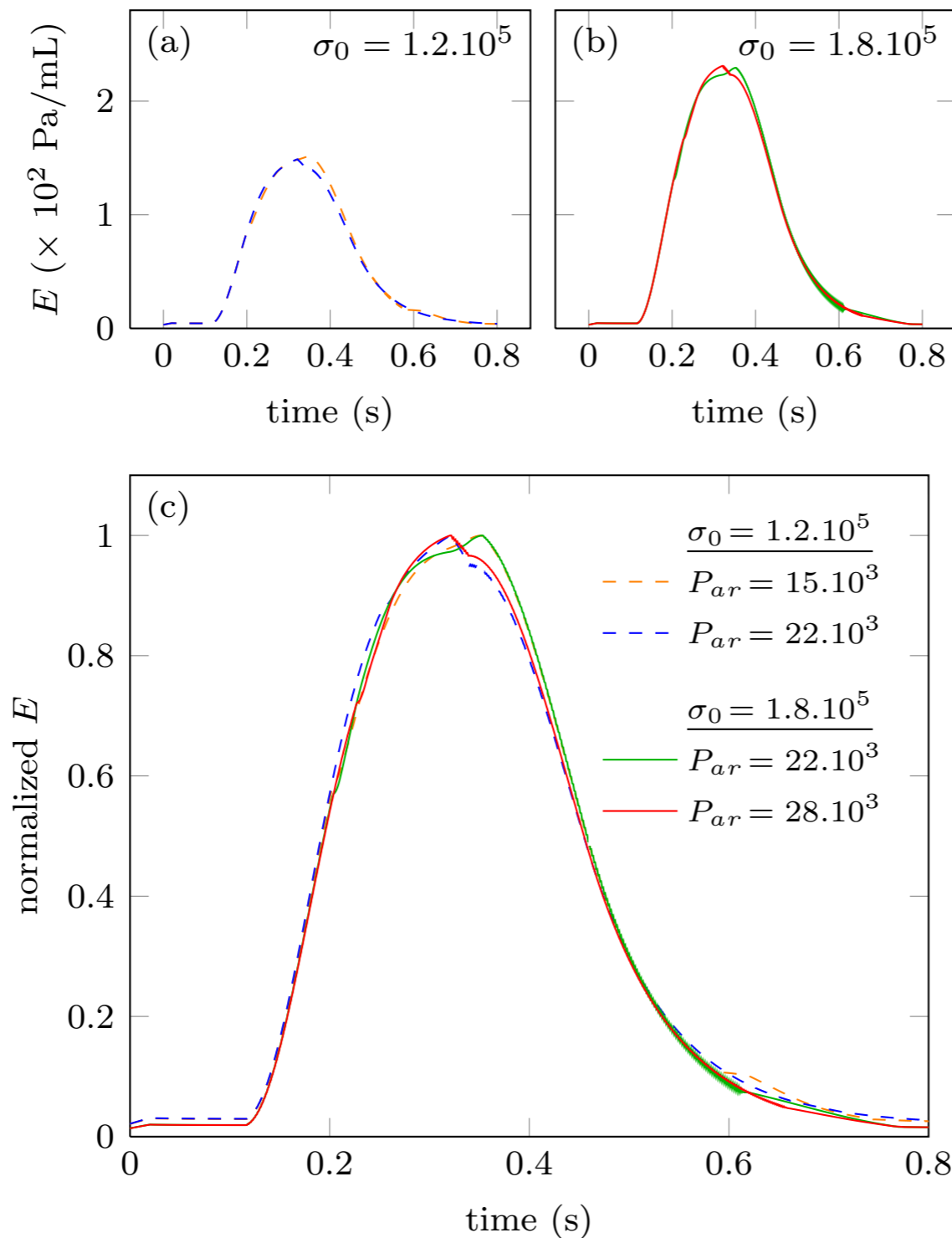
**Geometric param. adj. for left ventricle**

**Physical param. unchanged except contractility  $\times 10$**

# End-systolic pressure-volume relation (ESPVR) with simplified model



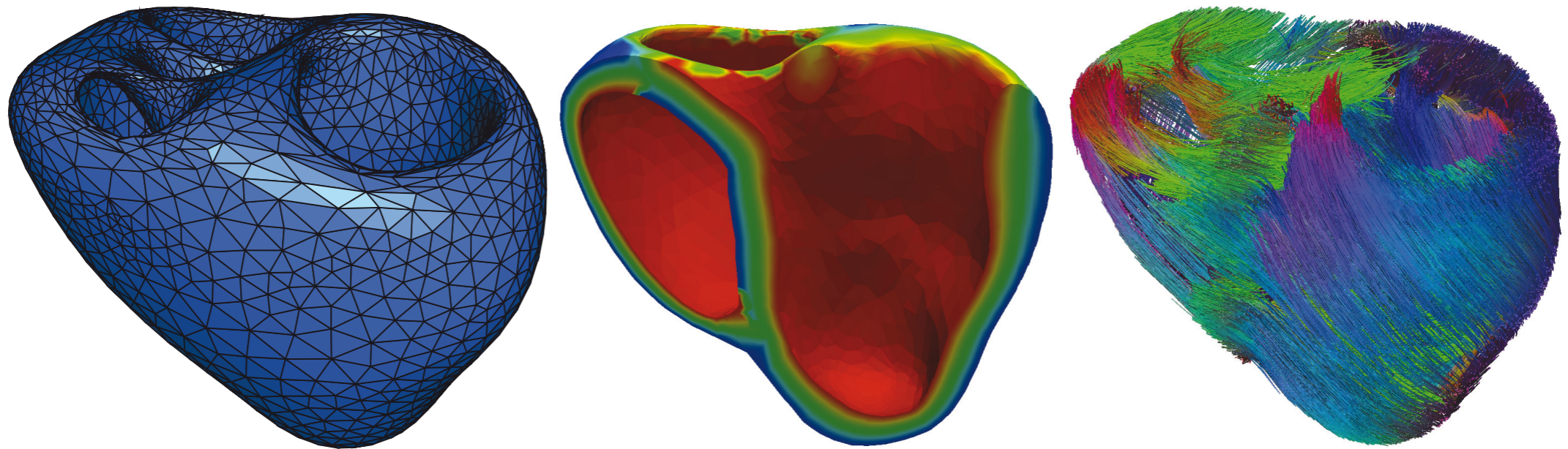
# Suga-Sagawa elastance signature



$$E(t) = \frac{P_v(t)}{V(t) - V_d}$$

# Modeling the organ heart

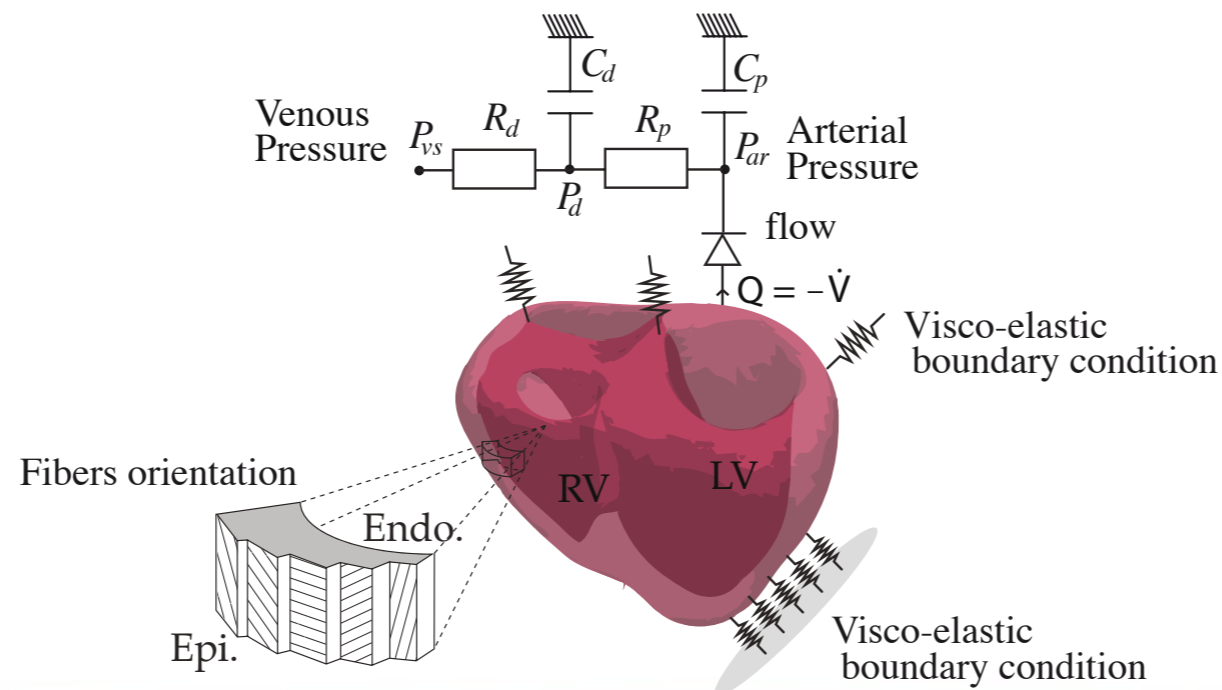
- Fiber directions: not quite at hand *in-vivo* yet, hence difficulty for *patient-specific* → prescribed based on anatomical knowledge



# Modeling the organ heart

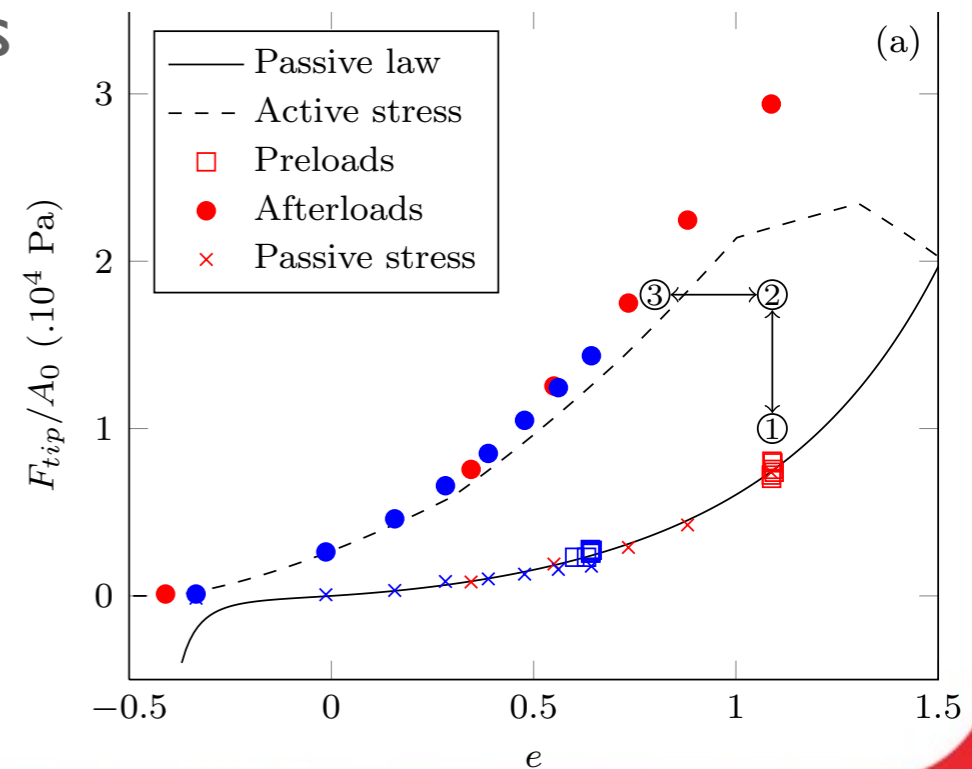
- Fiber directions: not quite at hand *in-vivo* yet, hence difficulty for *patient-specific* → prescribed based on anatomical knowledge
- Boundary conditions: complex interactions with surrounding structures and organs → viscoelastic support and sliding contact
- Closure of the system to account for pressure variables:

Windkessel model (0D) for artery flows



# Modeling the organ heart

- Fiber directions: not quite at hand *in-vivo* yet, hence difficulty for *patient-specific* → prescribed based on anatomical knowledge
- Boundary conditions: complex interactions with surrounding structures and organs → viscoelastic support and sliding contact
- Closure of the system to account for pressure variables:  
Windkessel model (0D) for artery flows
- Difficulty with reference configuration:  
end-diastole not stress-free  
→ *inverse problem* to be solved  
(Gee, Förster & Wall, IJNMBE, 2010)



# Cardiac Resynchronization Therapy patient-specific modeling... and optimization

*M. Sermesant, R. Chabiniok, P. Chinchapatnam, T. Mansi, F. Billet, P. Moireau, J.M. Peyrat, K. Wong, J. Relan, K. Rhode, M. Ginks, P. Lambiase, H. Delingette, M. Sorine, C.A. Rinaldi, D. Chapelle, R. Razavi and N. Ayache*  
**Patient-Specific Electromechanical Models of the Heart for the Prediction of Pacing Acute Effects in CRT: a Preliminary Clinical Validation**  
Medical Image Analysis, 16(1):201-215, 2012

# Protocol

## Patient

60 years old woman with congested heart failure (NYHA III) and LBBB

## Clinical intervention

Pacing using several resynchronization schemes (number and location of pacing leads, timing)

## Data

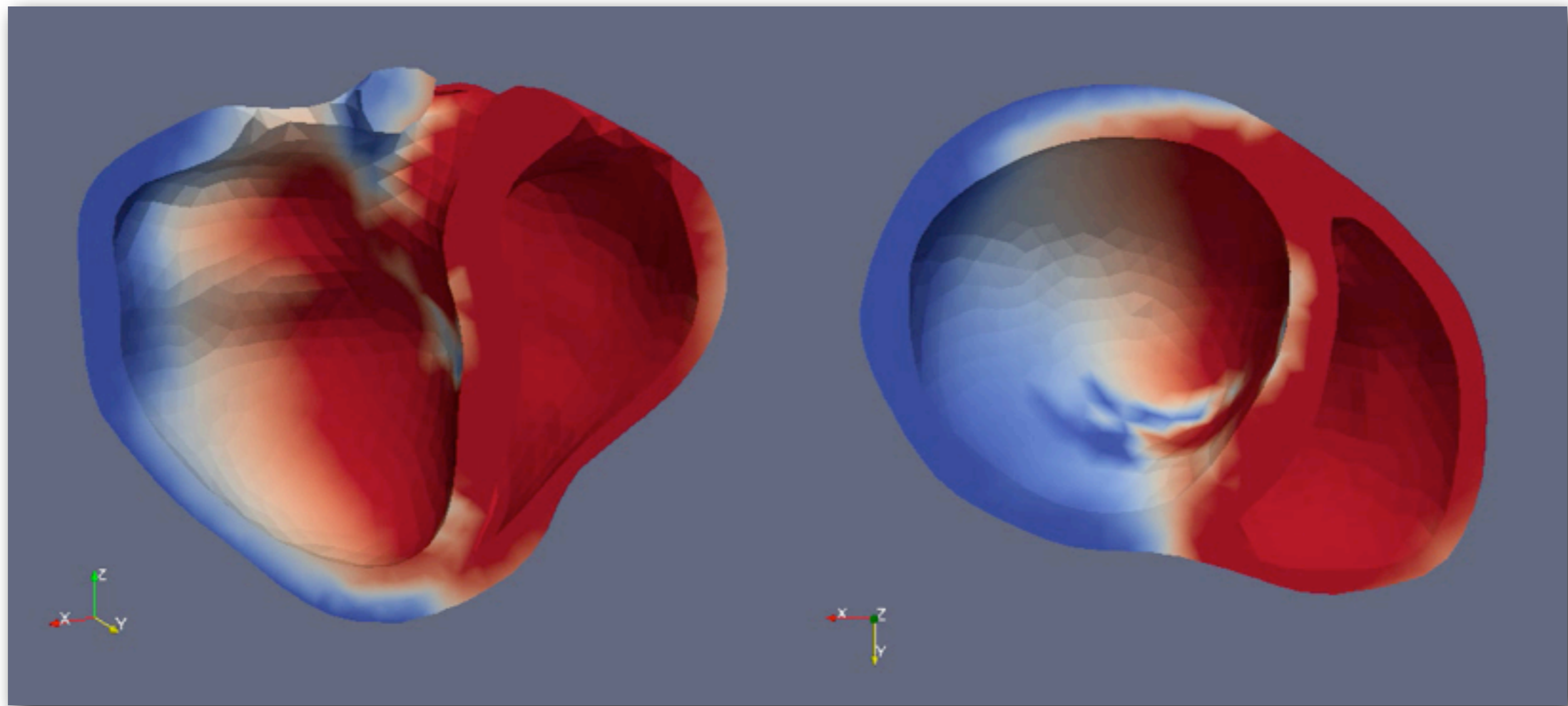
Non-contact electrophysiological mapping of the LV endocardial potentials using Ensite 3000 multi-electrode array catheter system (St Jude, Sylmar, CA)  
LV pressure measurements

## Objective

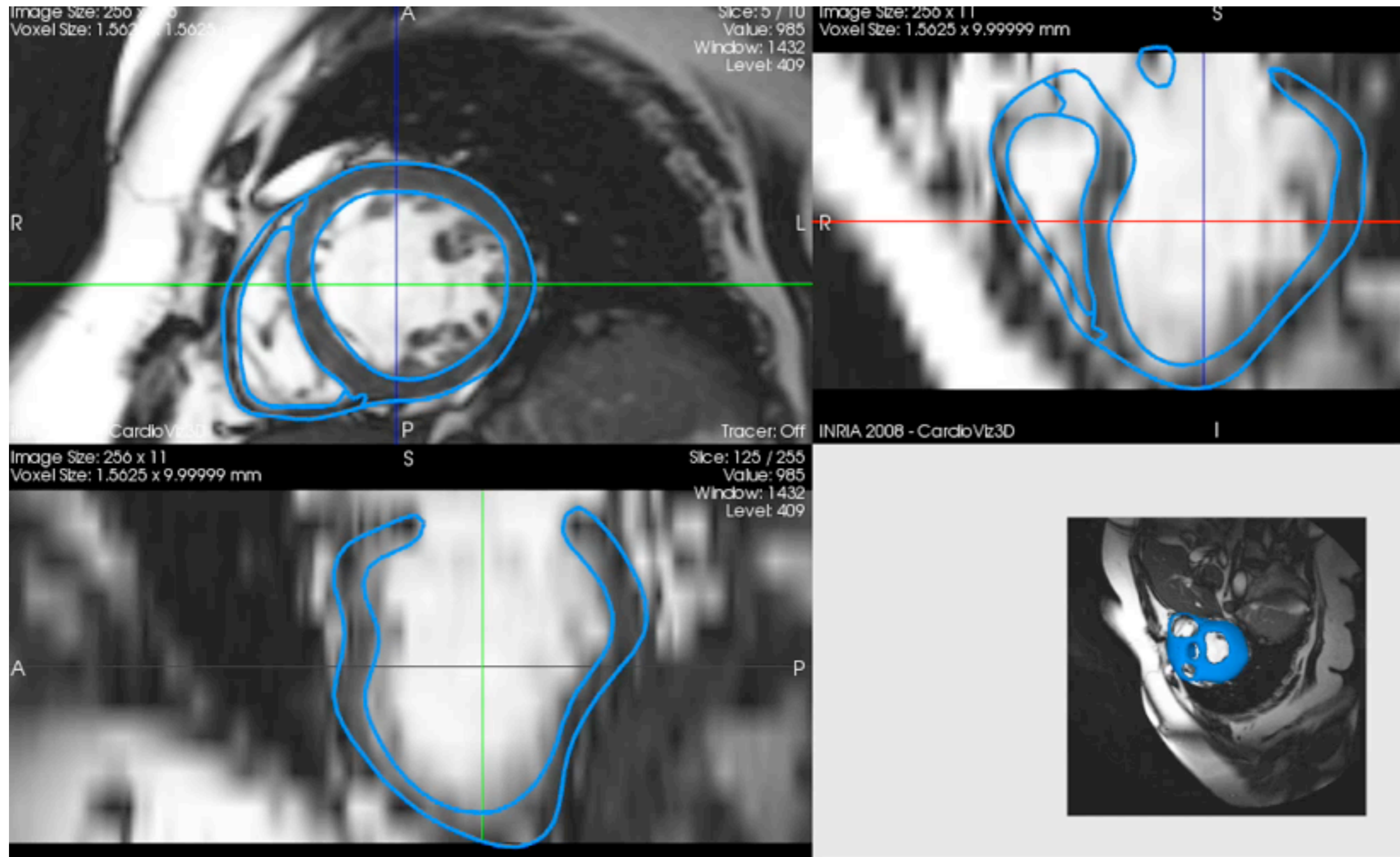
Short term effect of CRT can be assessed by measuring left ventricular pressure and its time derivative:

$$\max\left(\frac{dp}{dt}\right)$$

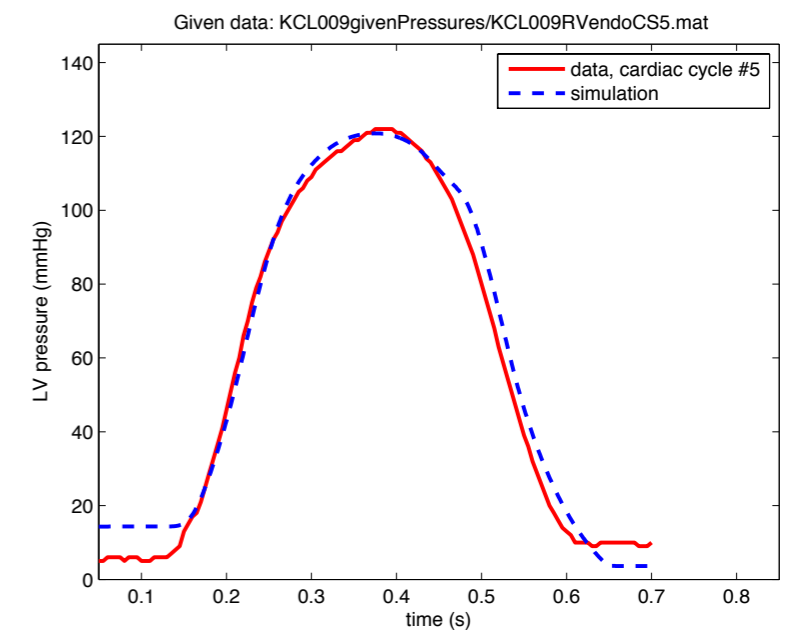
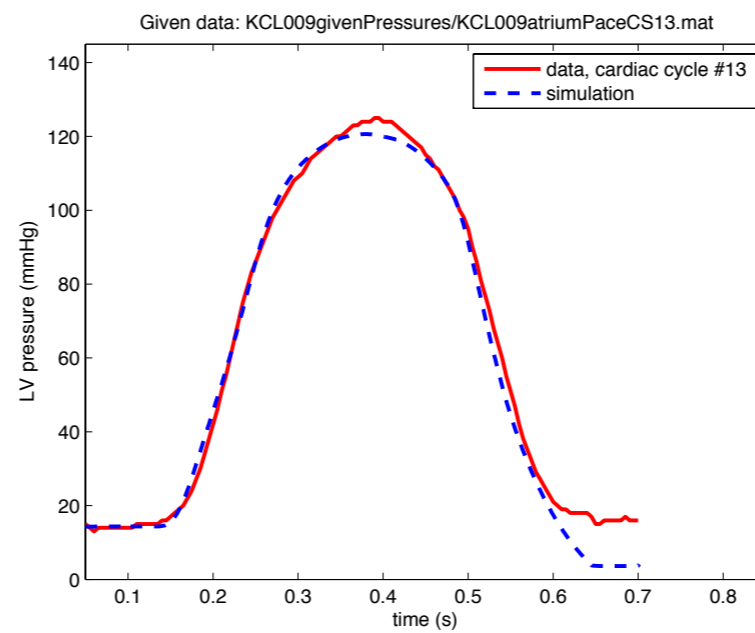
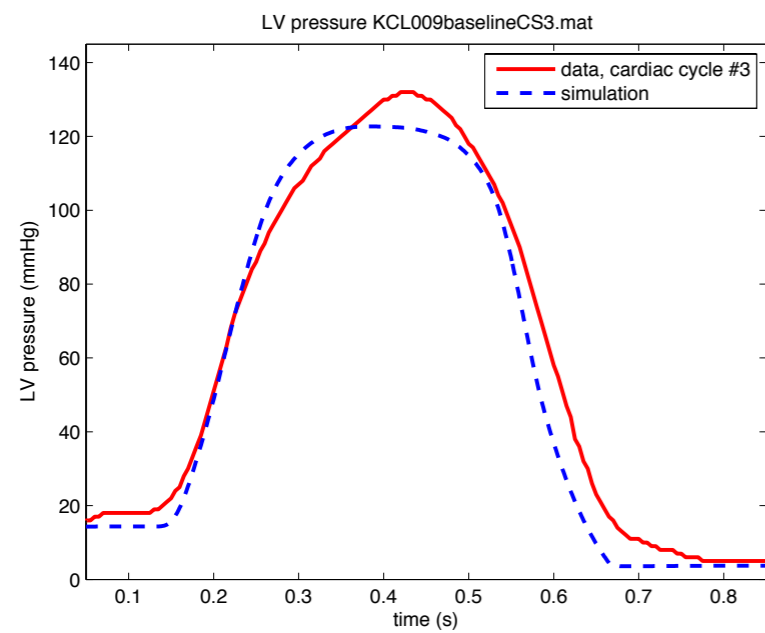
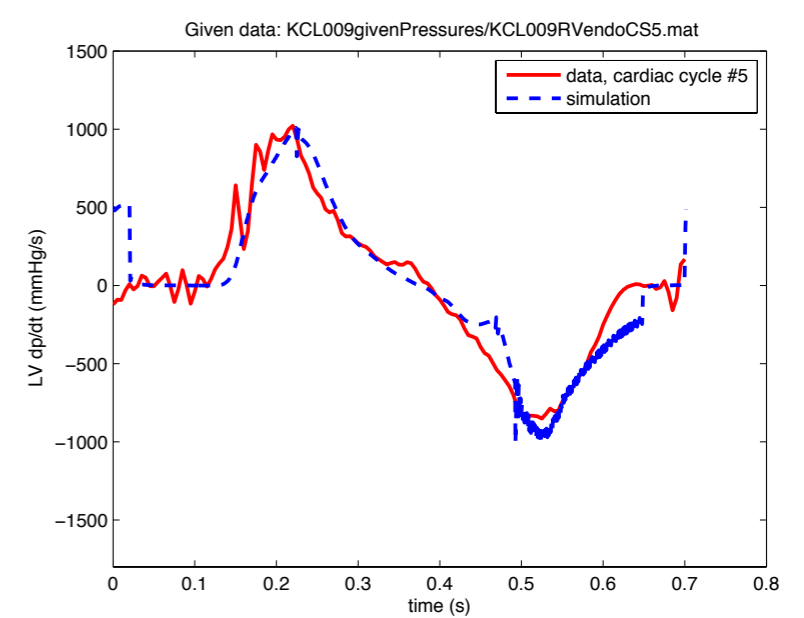
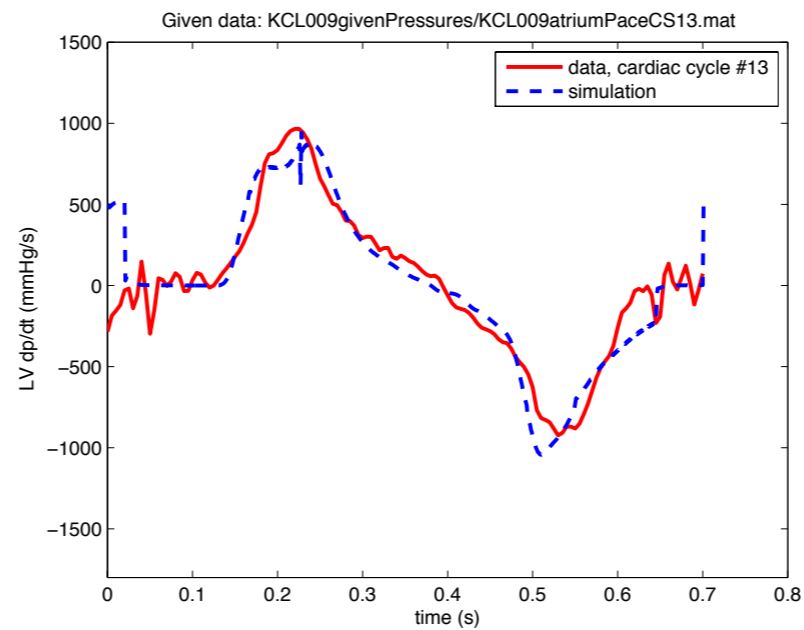
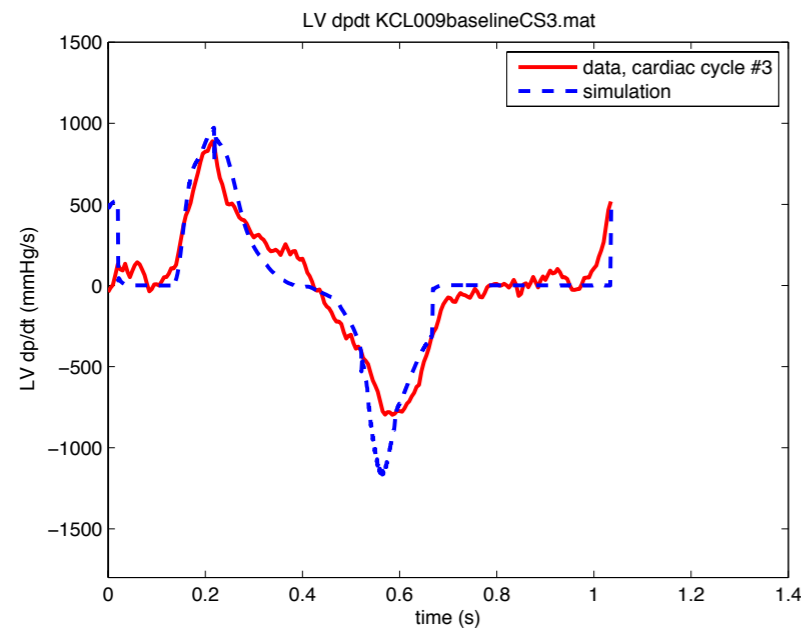
# Model Calibration - Baseline simulation



# Baseline simulation immersed in MRI



# Optimization of CRT procedure [1]



baseline (LBBB)

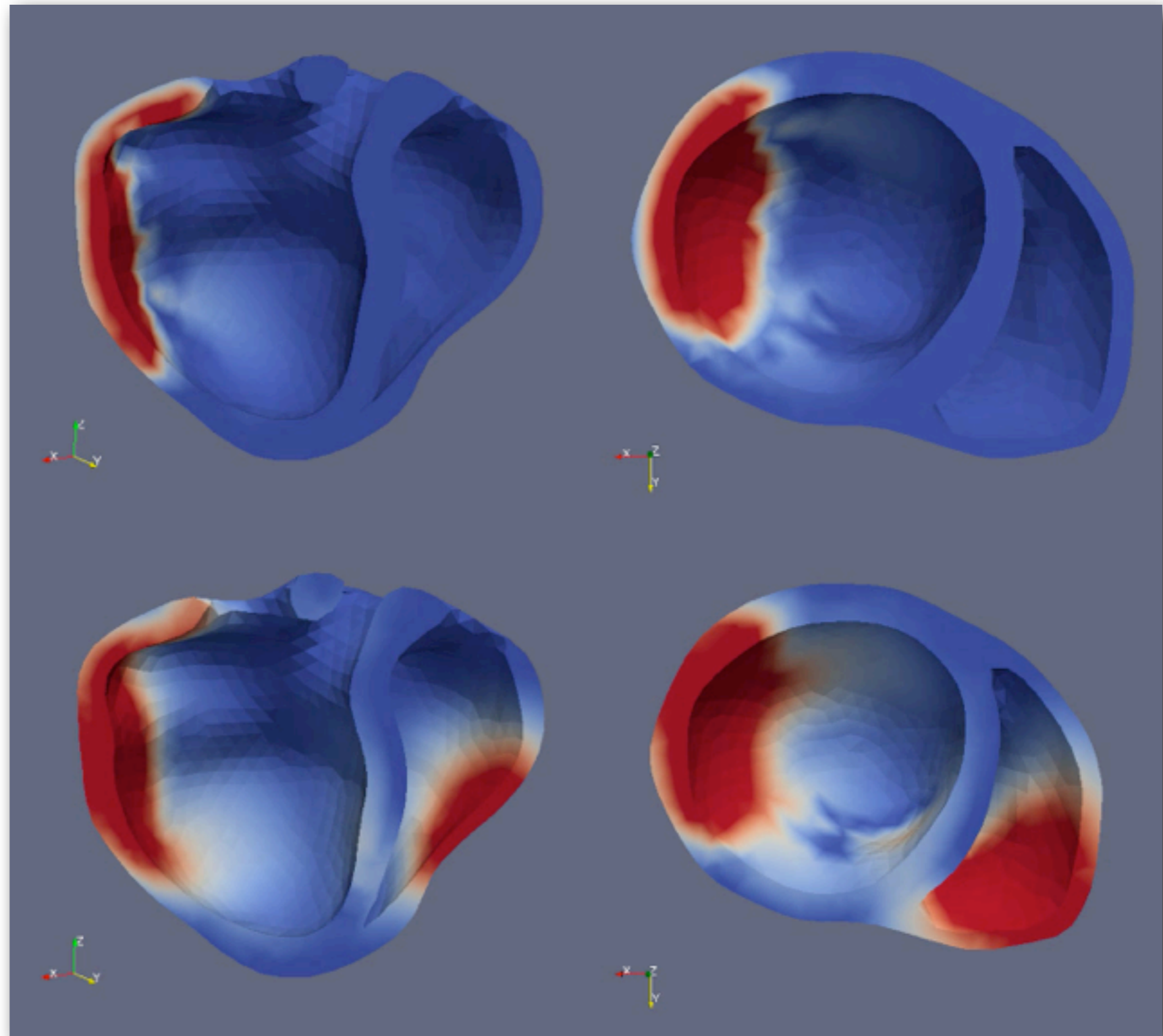
right atrial pacing

RV endo pacing

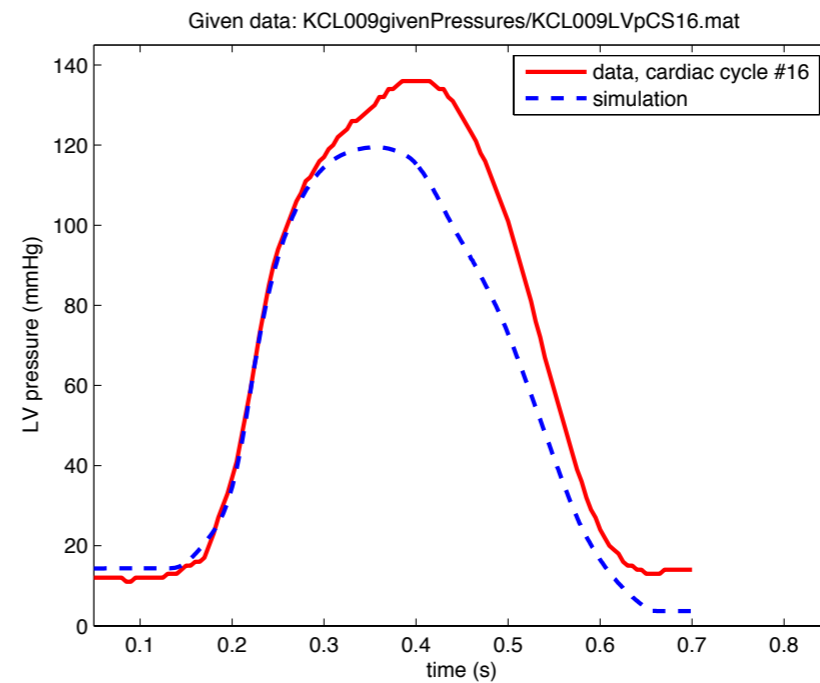
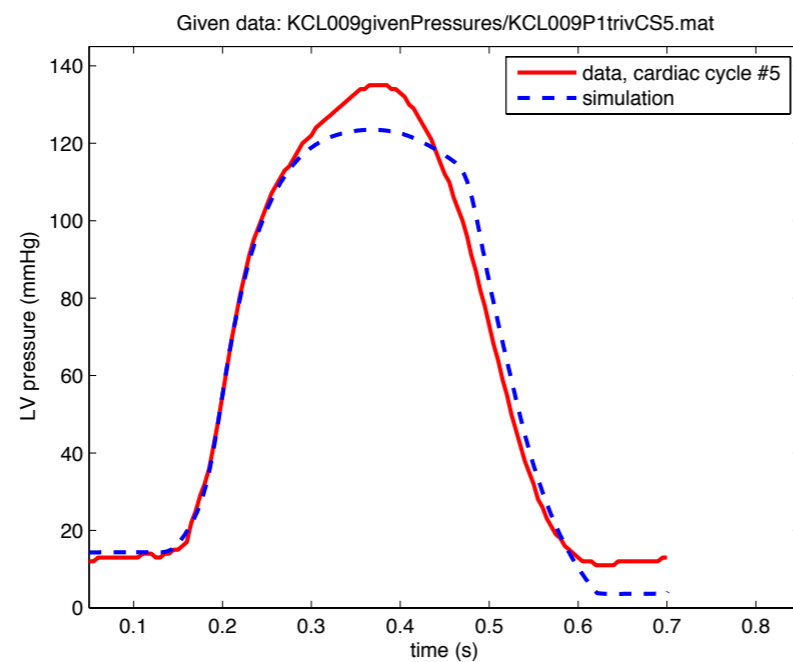
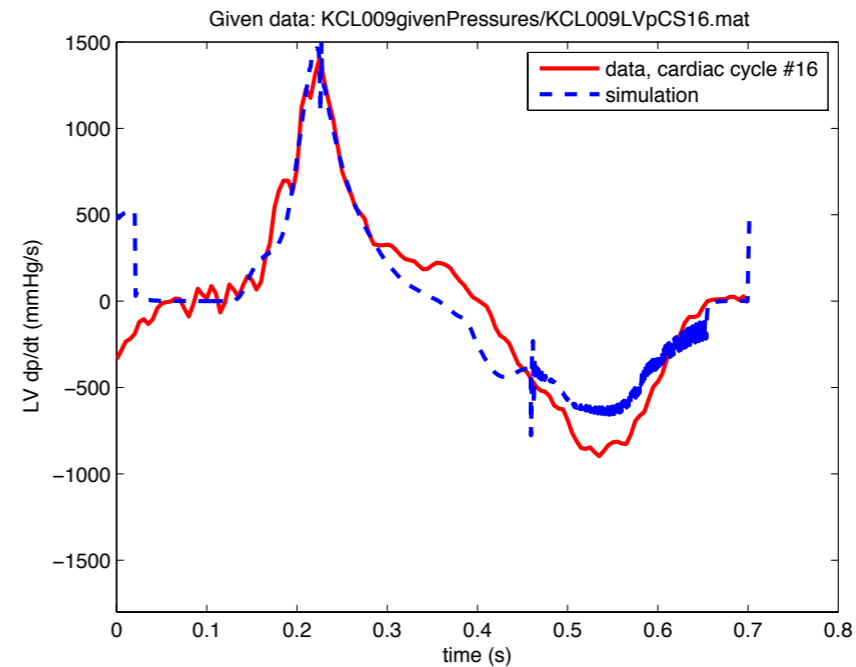
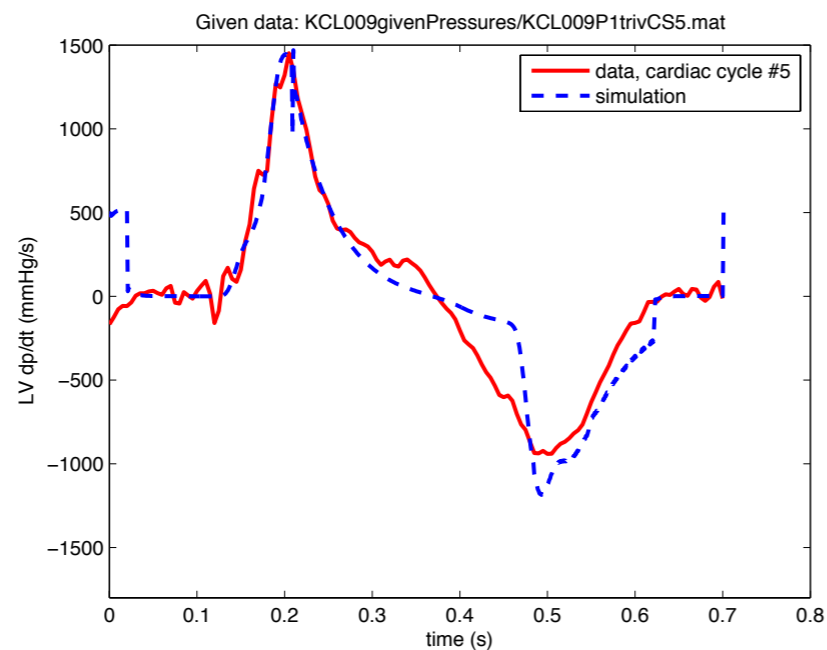
# Optimization of CRT: effective strategies

p1triv  
(LV endo, coronary  
sinus, RV endo)

LVp  
(LV endo)



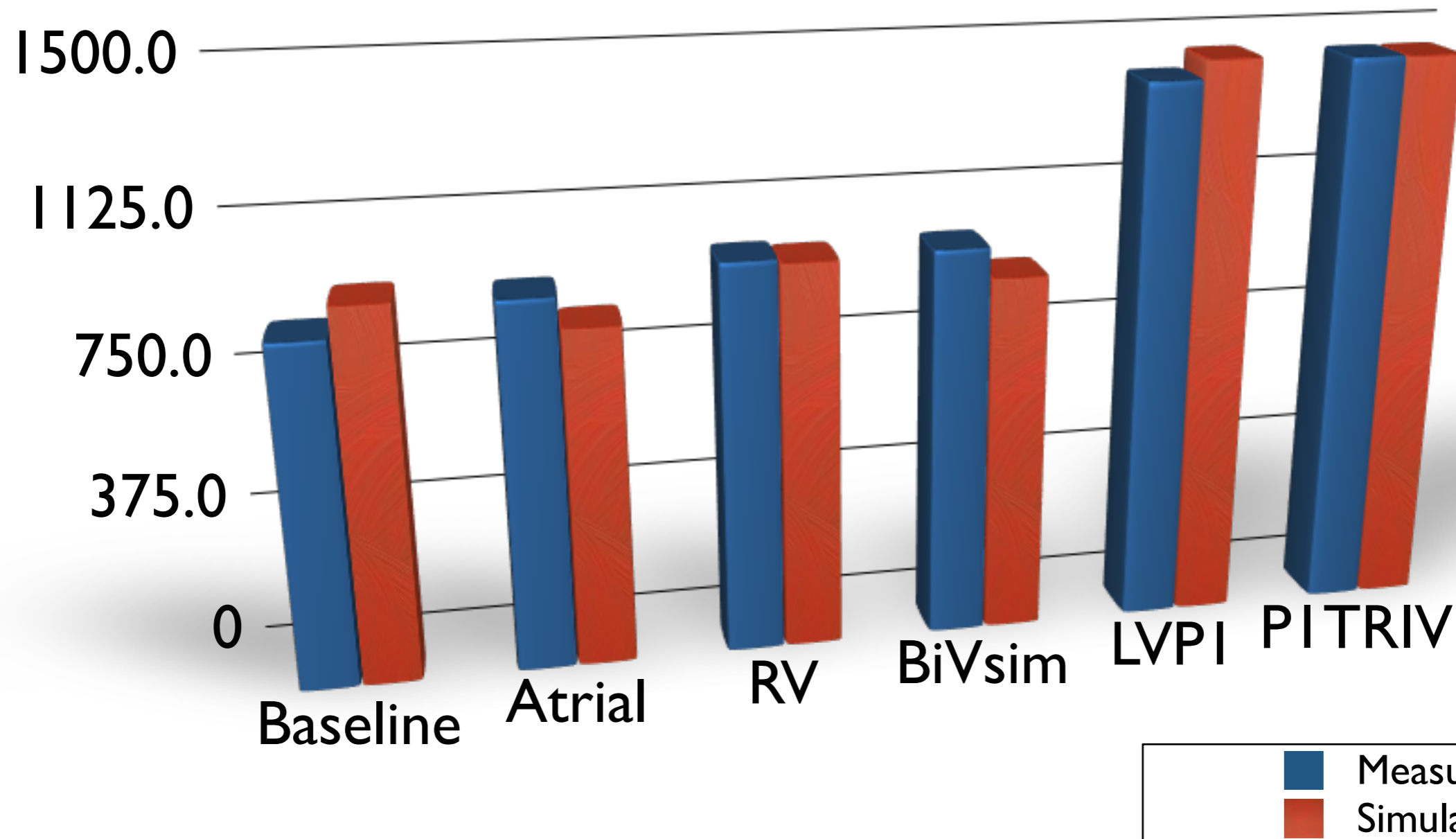
# Optimization of CRT procedure [2]



P1triv

LV endo pacing

$$\max \left( \frac{dp}{dt} \right) (mmHg/s)$$



# Estimation problem setup

## Models (dynamical system)

$$\dot{X} = A(X, \theta, t)$$

Arising from:  
solid / fluid mechanics, etc.

Equation types: PDEs, variational formulations (FEs), ODEs...

To be estimated:

$$X(0) \text{ and } \theta \rightarrow X$$

Typical sizes:

$X(0)$  :  $10^3$  to  $10^6$  dofs

$\theta$  : 10 to 100 parameters

## Measurements (images & signals)

$$Z = H(X) + \chi$$

in raw (?) or processed form, e.g.:

✓ MRI or US with segmentation and/or optical flow

✓ Tagged MRI with extracted displacements and/or velocity...

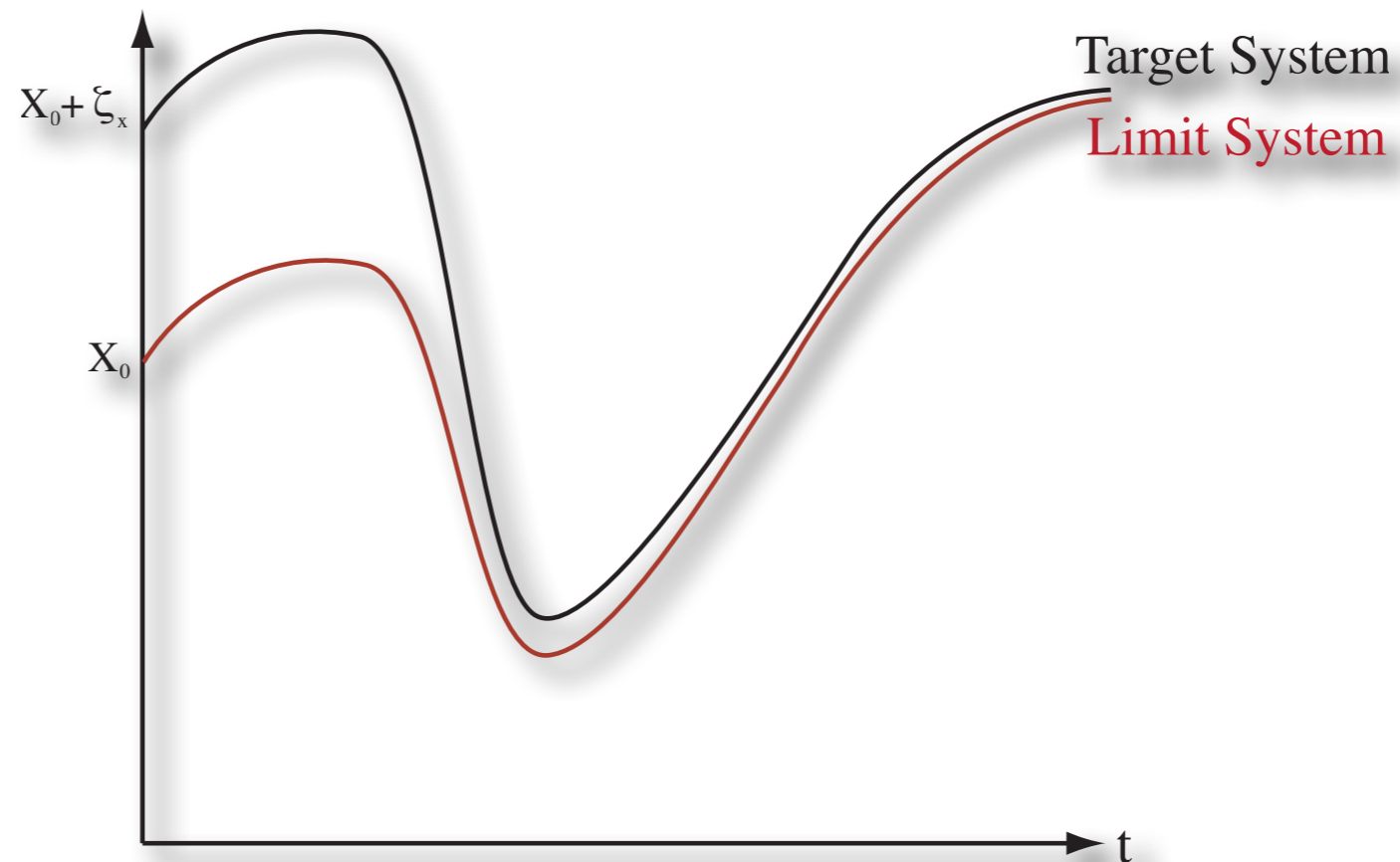
Note:

some modeling may be involved in pre-processing, statistical modeling in noise.

# Sequential data assimilation (filtering)

Basic principle:

$$\begin{aligned}\dot{X} &= A(X), \quad \text{with } X(0) = X_0 + \xi, \quad \text{but } Z = H(X) + \chi, \\ \dot{\hat{X}} &= A(\hat{X}) + K(Z - H(\hat{X})), \quad \text{with } \hat{X}(0) = X_0,\end{aligned}$$



# Sequential data assimilation (filtering)

Basic principle:

$$\begin{aligned}\dot{X} &= A(X), \quad \text{with } X(0) = X_0 + \chi, \quad \text{but } Z = H(X) + \chi, \\ \dot{\hat{X}} &= A(\hat{X}) + K(Z - H(\hat{X})), \quad \text{with } \hat{X}(0) = X_0,\end{aligned}$$

✓ **Kalman** equations for **optimal** filter (in linear case)

$$\begin{cases} \dot{\hat{X}}(t) = A\hat{X} + PH^T W^{-1} (Z - H\hat{X}) \\ \dot{P} - PA^T - AP + PH^T W^{-1} HP = 0 \\ P(0) = P_0 \\ \hat{X}(0) = X_0 \end{cases}$$

✓ In non linear case, you must solve a HJB equation,  
or an approximate “Extended Kalman Filter”

✓ **Major drawback:** computation of Kalman filter is untractable in  
practice (full covariance)

# Effective state estimators

## Luenberger observers:

Design  $K$  filter “easy to compute” and effective, i.e. fast  $\hat{X} \rightarrow X$  convergence

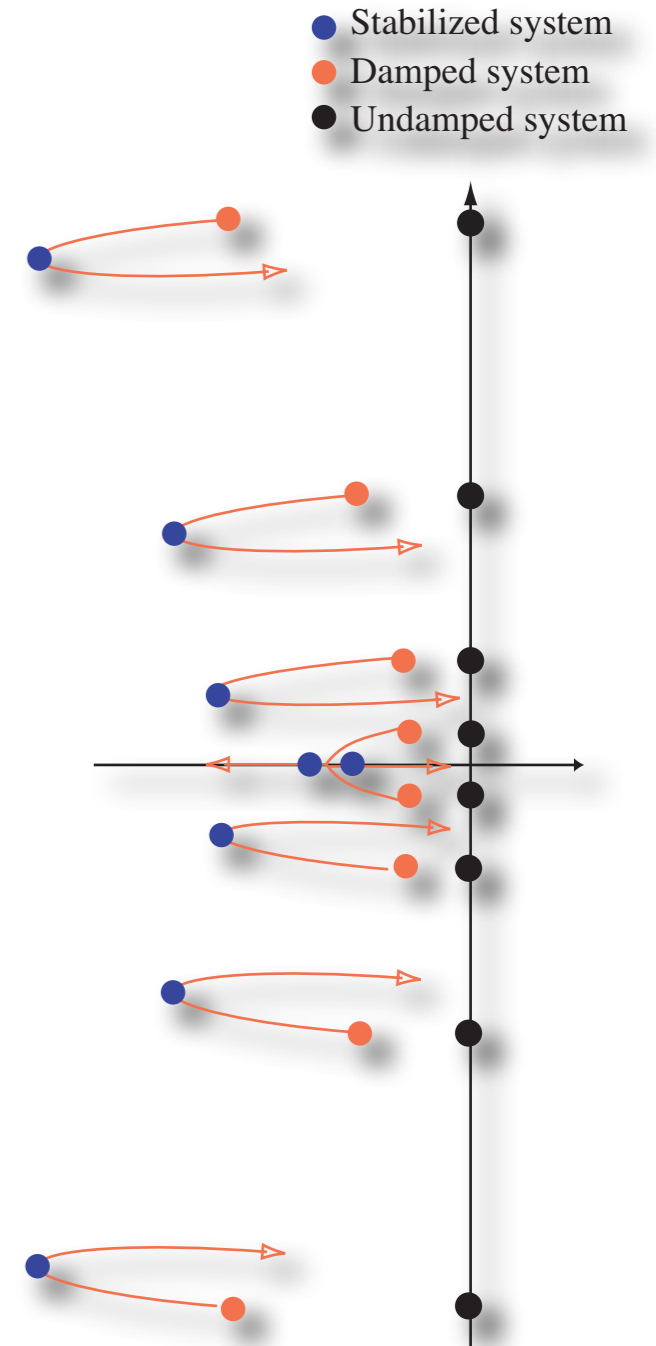
When  $A$  and  $H$  linear, error  $\tilde{X} = X - \hat{X}$  gives

$$\dot{\tilde{X}} = (A - KH)\tilde{X} - K\chi,$$

hence effective *feedback stabilization* provides adequate filter

## Advantages:

- ✓ Many dissipative feedbacks known for energy-preserving systems (or other invariants)
- ✓ *Physics-based* operators easy to implement in simulation software
- ✓ Reasonable cost (sparse operators)
- ✓ *Robustness* much preferable to “optimality”
- ✓ Here, the control is applied on a *virtual system*: more possibilities!



# Joint state-parameter estimation

Aim: estimate  $(\zeta_X, \theta)$  in  $\dot{X} = AX + B\theta + R$ , with  $X(0) = X_0 + \zeta_X$

Classical path: introduce *augmented* dynamical system

$$\begin{cases} \dot{X} = AX + B\theta + R, & \text{with } X(0) = X_0 + \zeta_X \\ \dot{\theta} = 0, & \text{with } \theta(0) = \theta_0 + \zeta_\theta \end{cases}$$

✓ Kalman filter applied to augmented system

$$\begin{cases} \dot{\hat{X}} = A\hat{X} + B\theta + R + K_{Kal}^X(Z - H\hat{X}), & \text{with } \hat{X}(0) = X_0 \\ \dot{\hat{\theta}} = K_{Kal}^\theta(Z - H\hat{X}), & \text{with } \hat{\theta}(0) = \theta_0 \end{cases}$$

✓ Kalman untractable, so here we wish to substitute  $K_{stab}$  for  $K_{Kal}^X$

✓ No physics-based filter available for *virtual* parameter dynamics

Key idea: *two-stage estimation* (optimal *reduced-order* for param.)

$$\begin{cases} \dot{\hat{X}} = A\hat{X} + B\theta + R + K_{stab}(Z - H\hat{X}) + \frac{\partial \bar{X}}{\partial \theta} \hat{\dot{\theta}}, & \text{with } \hat{X}(0) = X_0 \\ \dot{\hat{\theta}} = K_{Kal}^{\theta b}(Z - H\hat{X}), & \text{with } \hat{\theta}(0) = \theta_0 \end{cases}$$

# ***Joint estimation bibliography***

- ✓ Moireau, Chapelle & Le Tallec: Joint state and parameter estimation for distributed mechanical systems. *CMAME*, 2008
- ✓ Chapelle, Moireau & Le Tallec: Robust filtering for joint state parameter estimation for distributed mechanical systems. *DCDS/A*, 2009
- ✓ Moireau & Chapelle: Reduced-order Unscented Kalman Filtering with application to parameter identification in large-dimensional systems. *ESAIM: COCV*, 2010
- ✓ Moireau, Chapelle & Le Tallec: Filtering for distributed mechanical systems using position measurements: perspectives in medical imaging. *Inverse Problems*, 2009

# Infarct characterization (by estimation)

*R. Chabiniok, P. Moireau, P.-F. Lesault, A. Rahmouni, J.-F. Deux and D. Chapelle*

**Estimation of tissue contractility from cardiac cine-MRI using a biomechanical heart model**

Biomechanics and Modeling in Mechanobiology, 11(5):609-630, 2012

# ***Protocol***

## **Subject**

Animal data obtained with a farm pig of 25kg (the study was approved by Institutional Animal Care and Use Committee of “Faculté de Créteil”)

## **Infarction protocol**

Healthy heart at T0: Baseline

Infarct creation by a 2-hour occlusion of the LAD coronary artery by a balloon catheter

Follow-up of the animal 10 days (T0+10) and 38 days (T0+38) after the infarct creation

## **Data**

**Cine MRI**, Late Enhancement (ground truth), Tagged MRI (optional), ECG

## **Objective of patient-specific modeling**

Locate (compare with LE) and characterize the infarct tissue (contractility)

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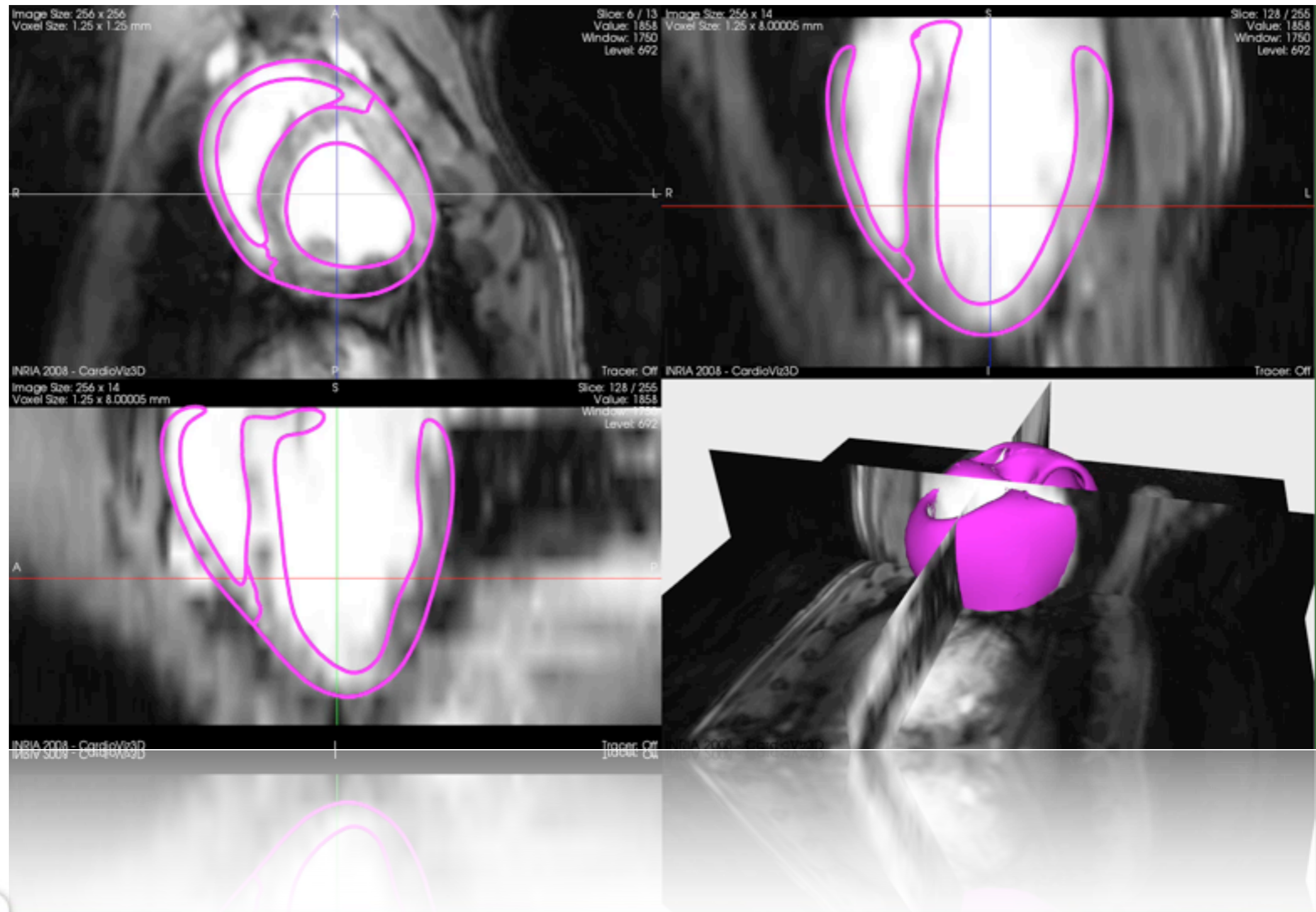
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## Objective of patient-specific modeling

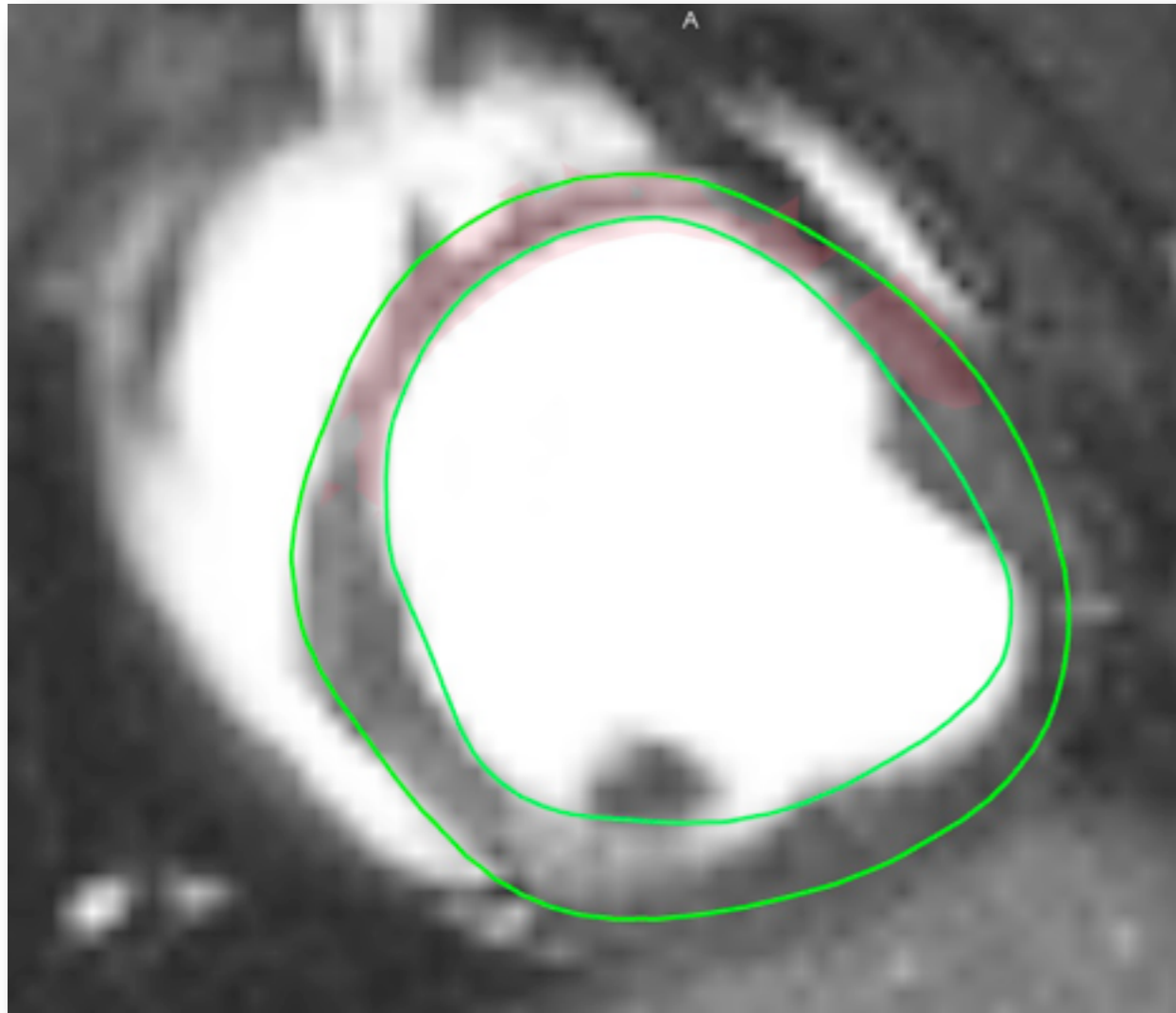
Locate (compare with LE) and characterize the infarct tissue (contractility)

$$\begin{cases} \dot{k}_c = -(|u| + \alpha |\dot{e}_c|)k_c + n_0 k_0 |u|_+ \\ \dot{\tau}_c = -(|u| + \alpha |\dot{e}_c|)\tau_c + \dot{e}_c k_c + n_0 \sigma_0 |u|_+ \end{cases}$$

# Model calibration for baseline (T0)



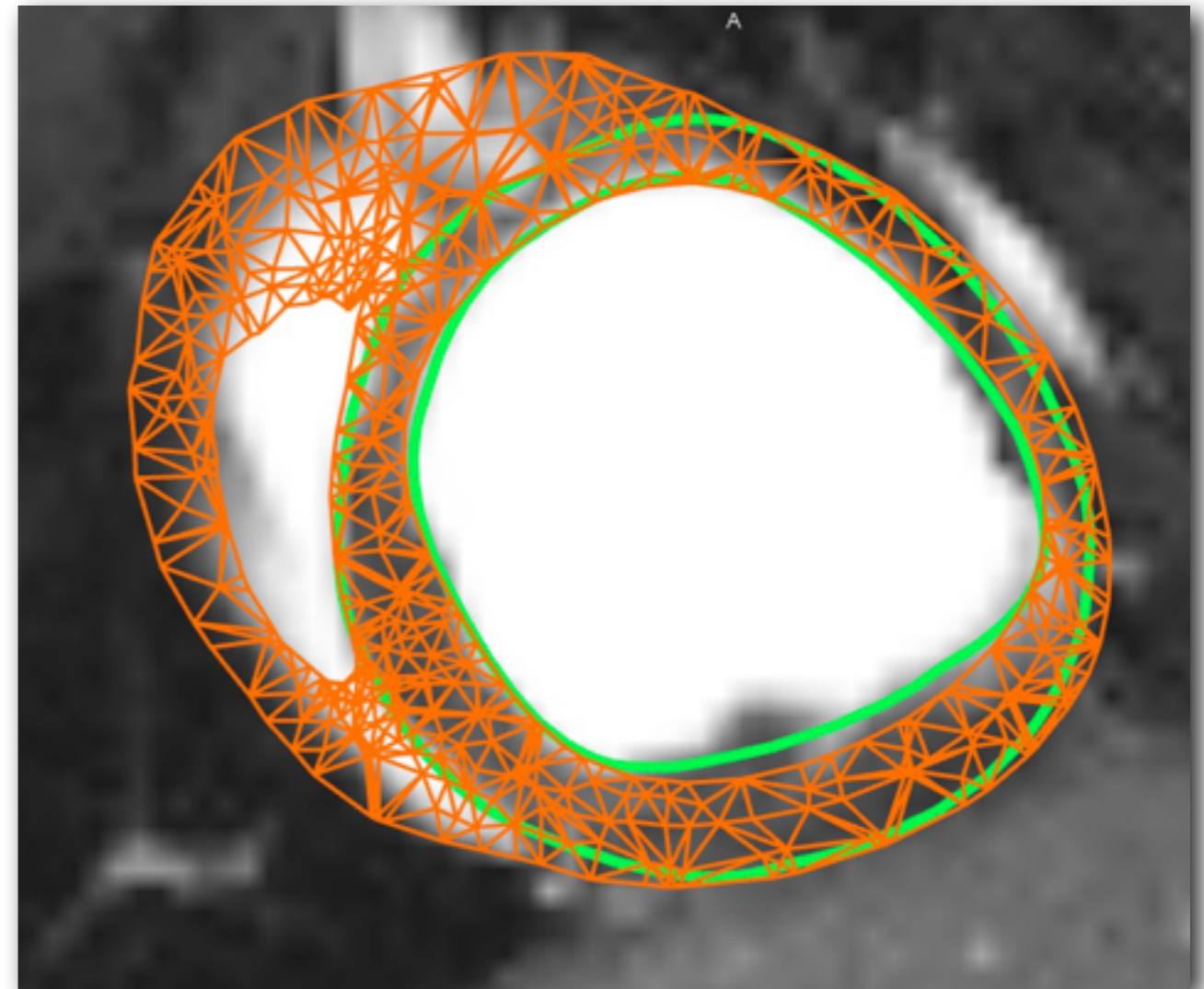
## ***Baseline (T0) compared to T38***



— Image contours  
extraction

— Model without  
infarct modeling

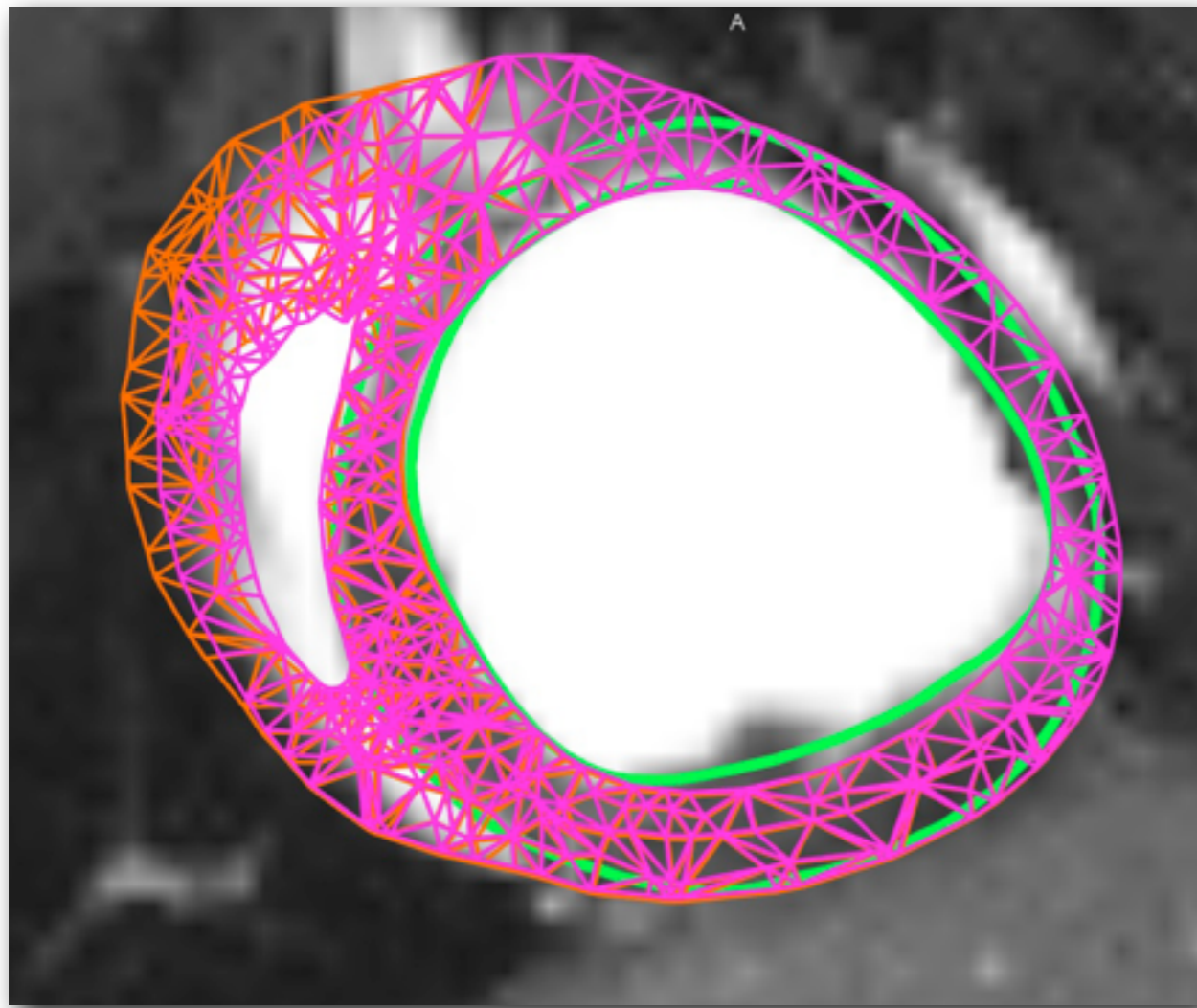
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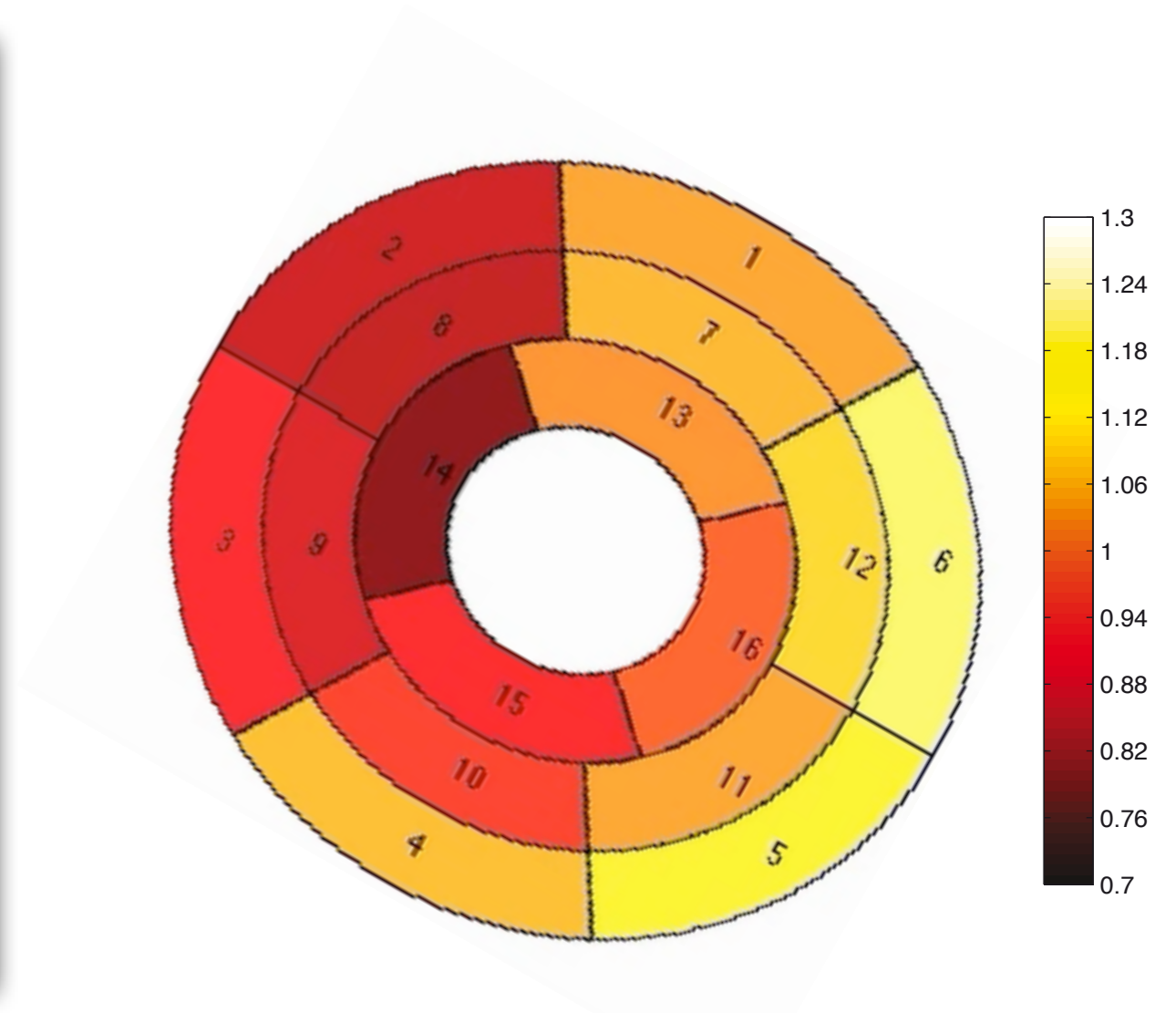
— Image contours  
extraction

— Model without  
infarct modeling

## *Estimation at work (actual cine-MR data)*

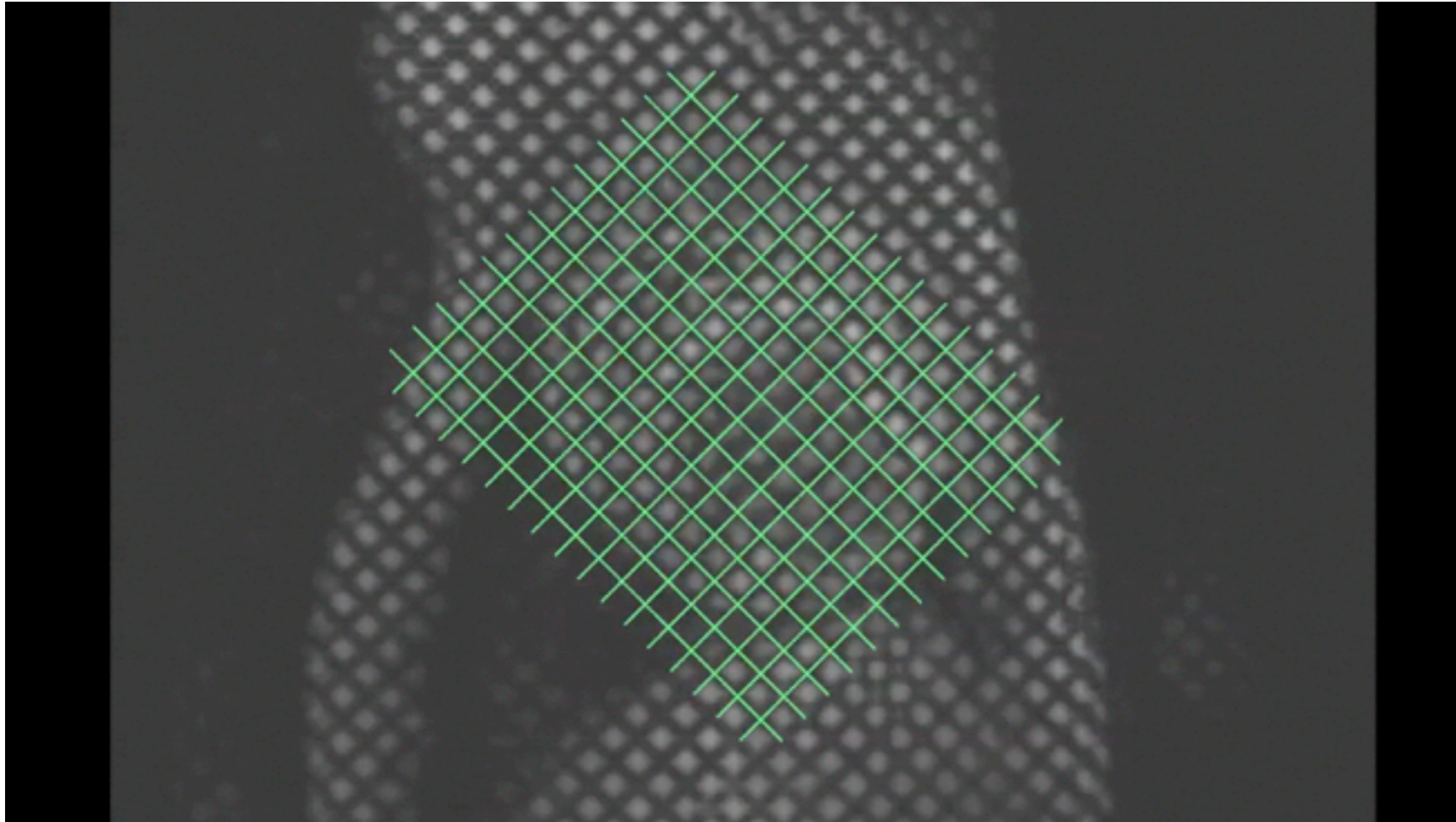


— **Estimator**



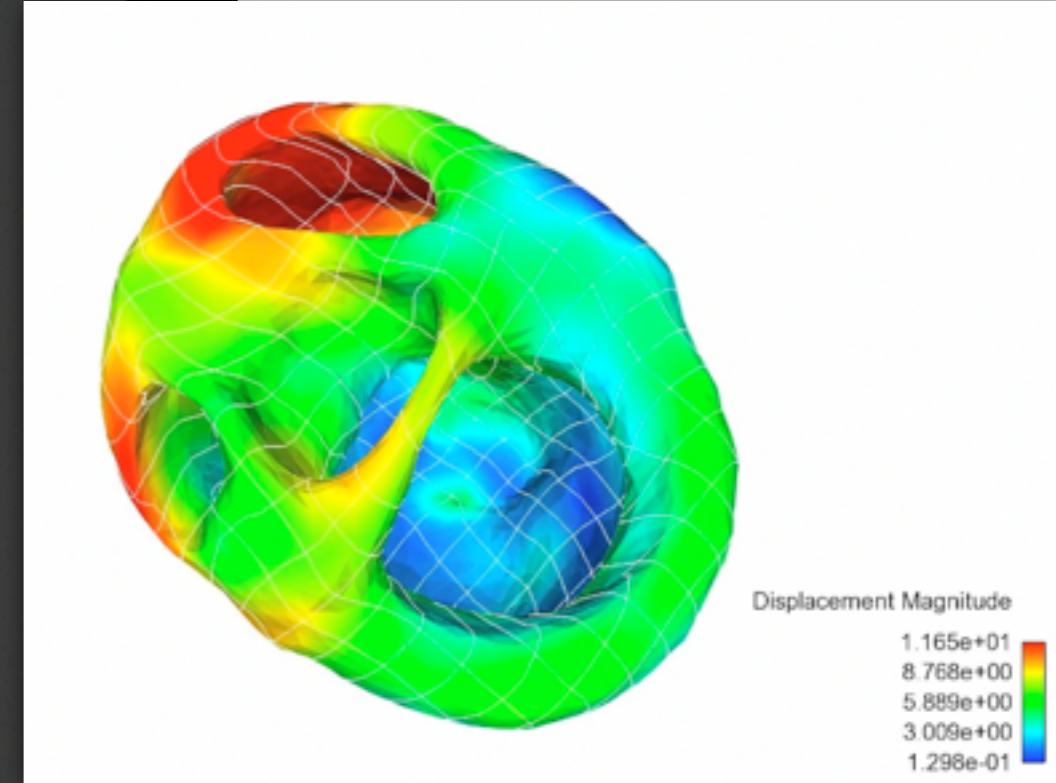
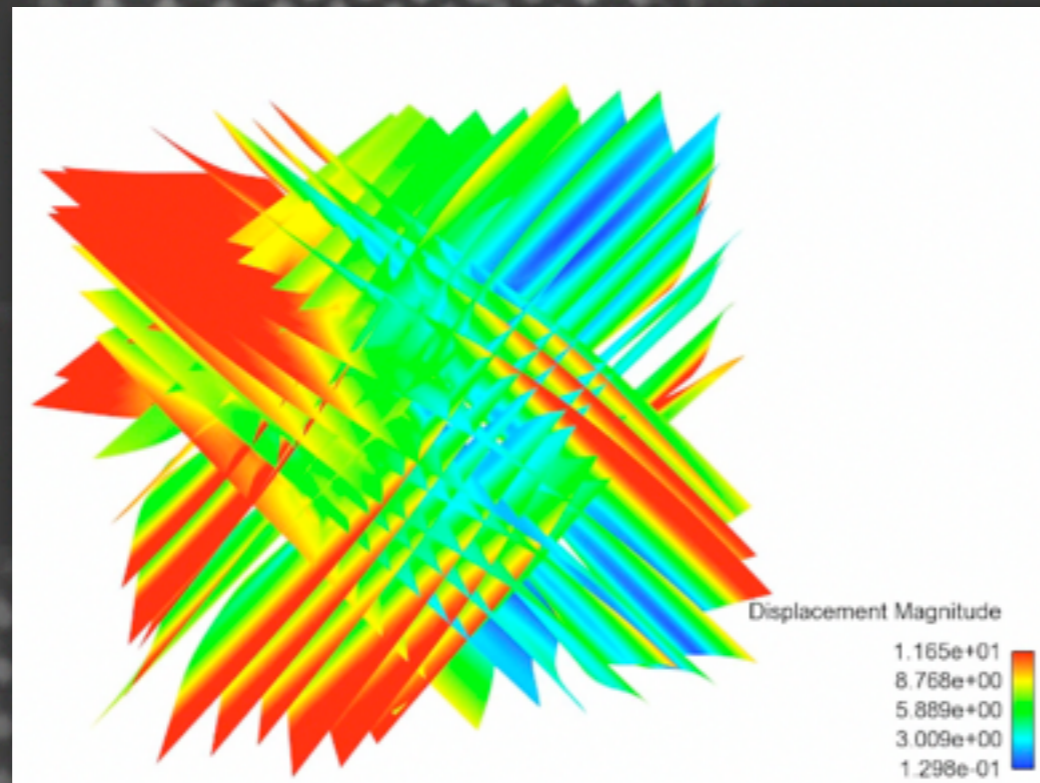
**Estimated contractility  
in AHA regions**

# *Enhanced estimation based on tagged-MR*



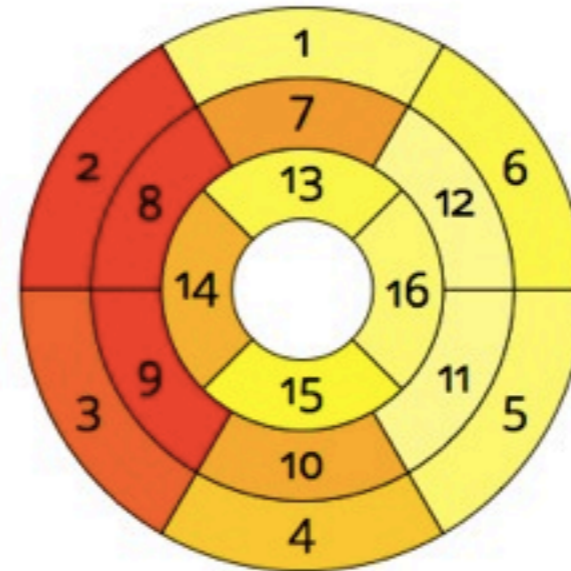
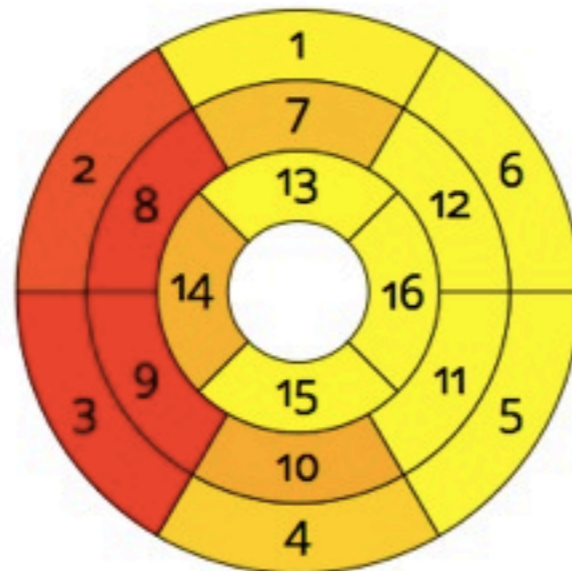
**PhD A. Imperiale**  
**Collaboration Creatis (INSA-Lyon)**

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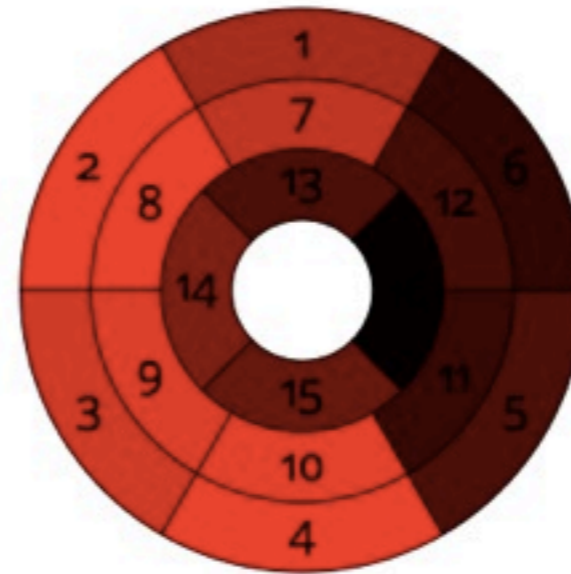
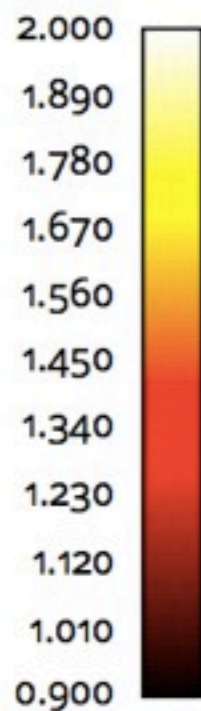


**PhD A. Imperiale**  
**Collaboration Creatis (INSA-Lyon)**

# Tagged-MR estimation results (synthetic)



**Contractility**



**Stiffness**

# Concluding remarks

- Multiscale modeling of the myocardium based on physiological considerations at all scales (starting with nano-scale)
- Fundamental physical requirements (energy) satisfied throughout the scales, and associated consistent numerical procedures  
→ well-adapted to multi-physics coupling (e.g. perfusion and chemistry)
- Substantial experimental and clinical validation achieved
- *Inverse problems* handled via novel effective data assimilation methods  
→ provide key information for *diagnosis* and allow *patient-specific modeling*



The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 224495