

Image-based modeling of the cardiovascular system

C. Alberto Figueroa, PhD

Edward B. Diethrich M.D. Associate Professor of Surgery and Biomedical Engineering

University of Michigan

Honorary Senior Lecturer in Biomedical Engineering

King's College London

CEMRACS 2015 Summer School

CIRM - Luminy

July 20th – 21st 2015



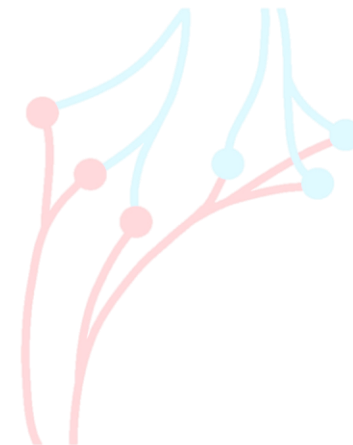
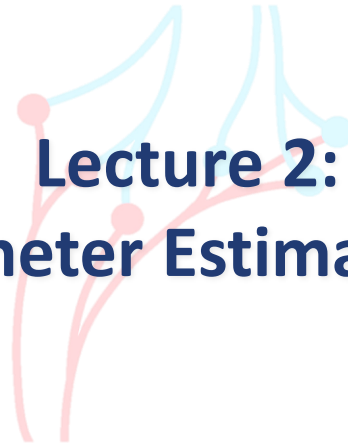
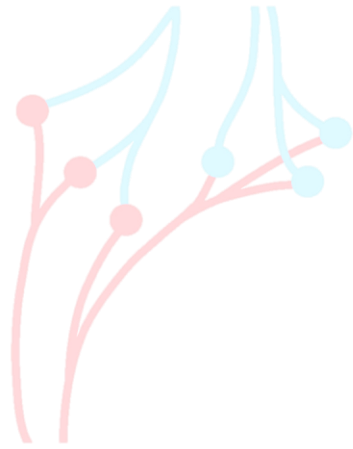
**COLLEGE OF ENGINEERING & MEDICAL SCHOOL
COMPUTATIONAL VASCULAR BIOMECHANICS LAB**
UNIVERSITY OF MICHIGAN



University of London

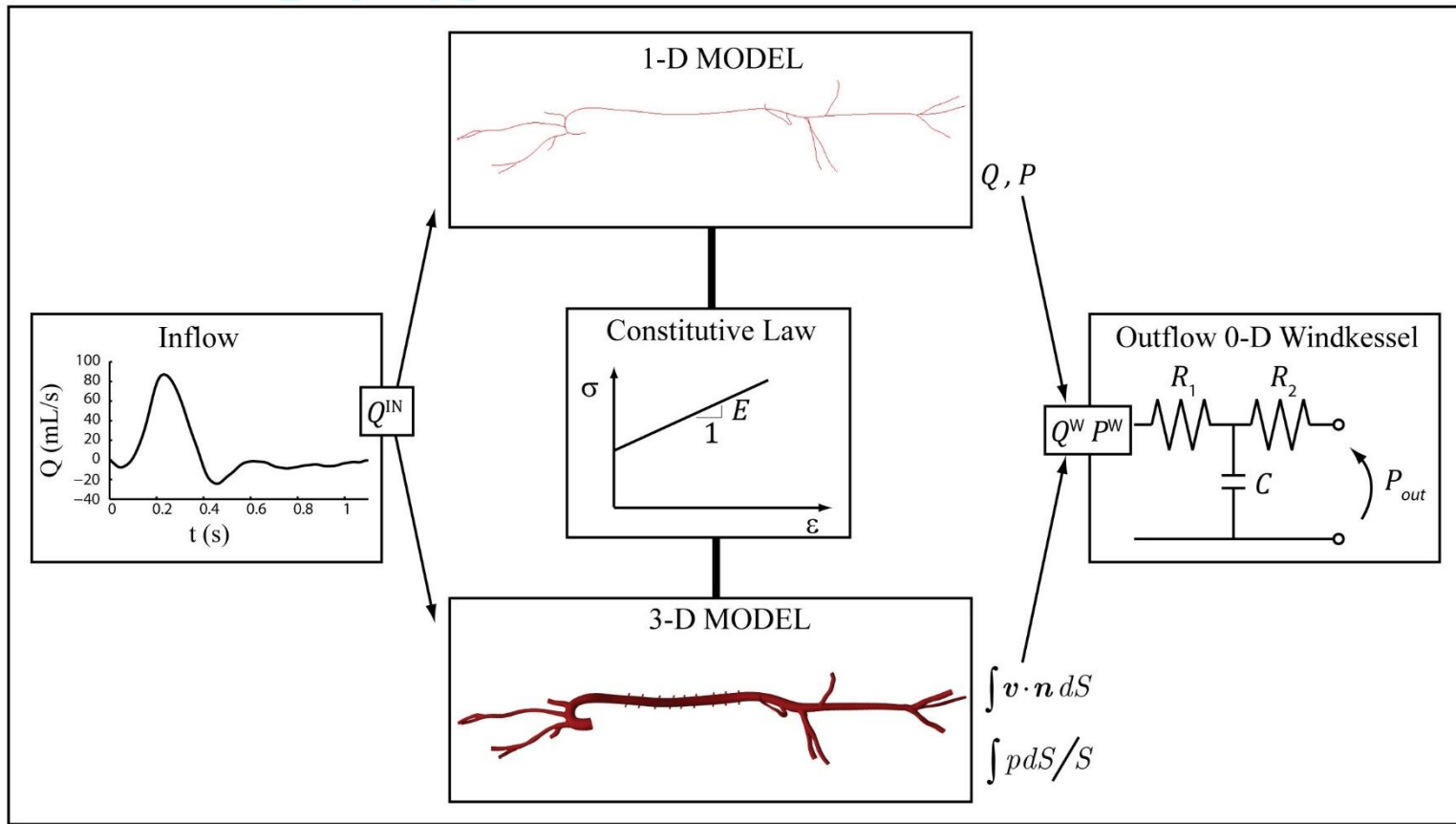
Outline

- Lecture 1: Introduction to function and modeling of the CV system
- Lecture 2: Techniques for Parameter Estimation in the CV system
- Lecture 3: Simulation of Transitional Physiology
- Lecture 4: Advanced Topics, Clinical Applications and Challenges



Lecture 2: Techniques for Parameter Estimation in the CV system

A combined 1D-3D framework for fast parameter estimation



Xiao, Alastruey, Figueroa, IJNMBE, 2014

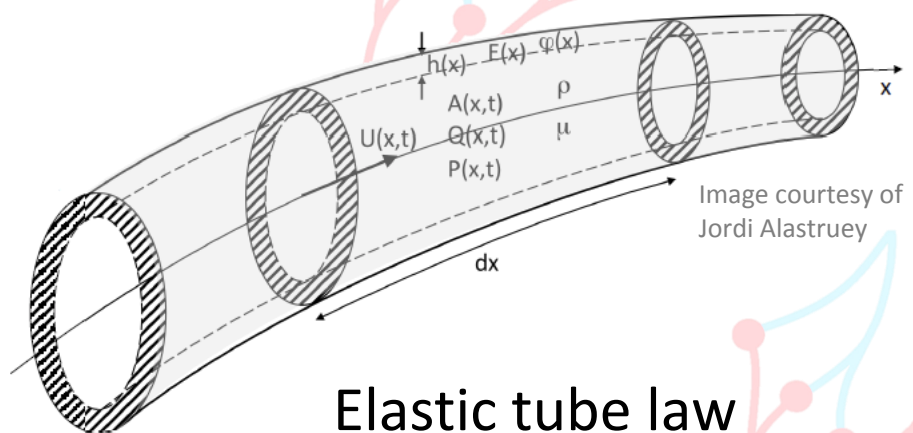
- 1-D “equivalent” surrogate model
- Identical inflow and Windkessel outflow BC
- Equivalent linear elastic vessel wall constitutive law

A combined 1D-3D framework for fast parameter estimation

Cross-sectional area Average axial velocity

Mass conservation: $\frac{\partial A}{\partial t} + \frac{\partial(AU)}{\partial x} = 0$ Frictional force/length

Momentum conservation: $\frac{\partial U}{\partial t} + U \frac{\partial U}{\partial x} + \frac{1}{\rho_f} \frac{\partial P}{\partial x} = \frac{f}{\rho_f A}$

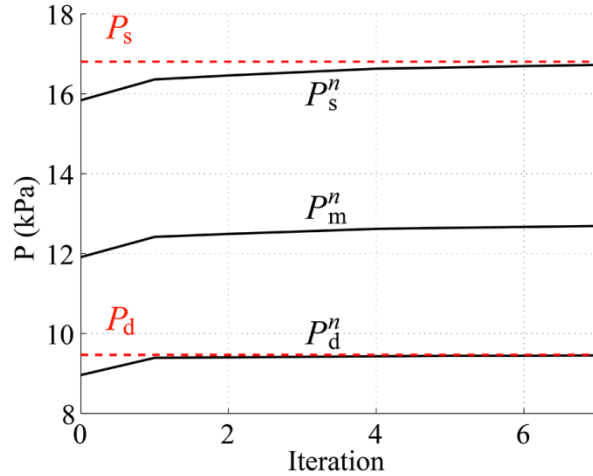


$$P = P_d + \frac{4}{3} Eh \frac{r - r_d}{(r_d)^2} = P_d + \frac{\beta}{A_d} (\sqrt{A} - \sqrt{A_d}), \quad \beta = \frac{4}{3} \sqrt{\pi} Eh$$

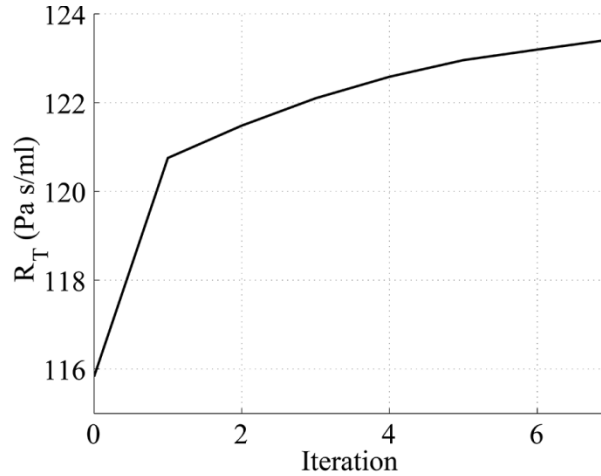
© C. Alberto Figueroa – figueroc@med.umich.edu

Iterative approach for tuning outflow BCs in 1D model

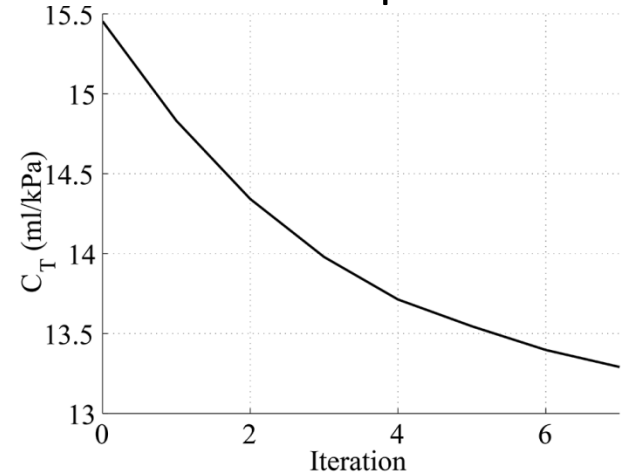
Pressures



Total Resistance



Total Compliance



$$R_T^{n+1} = R_T^n + \frac{\Delta P_m^n}{\bar{Q}_{in}}$$

Target diastolic pressure

$$\Delta P_m^n = P_d - P_d^n$$

Diastolic pressure after the n th 1-D simulation

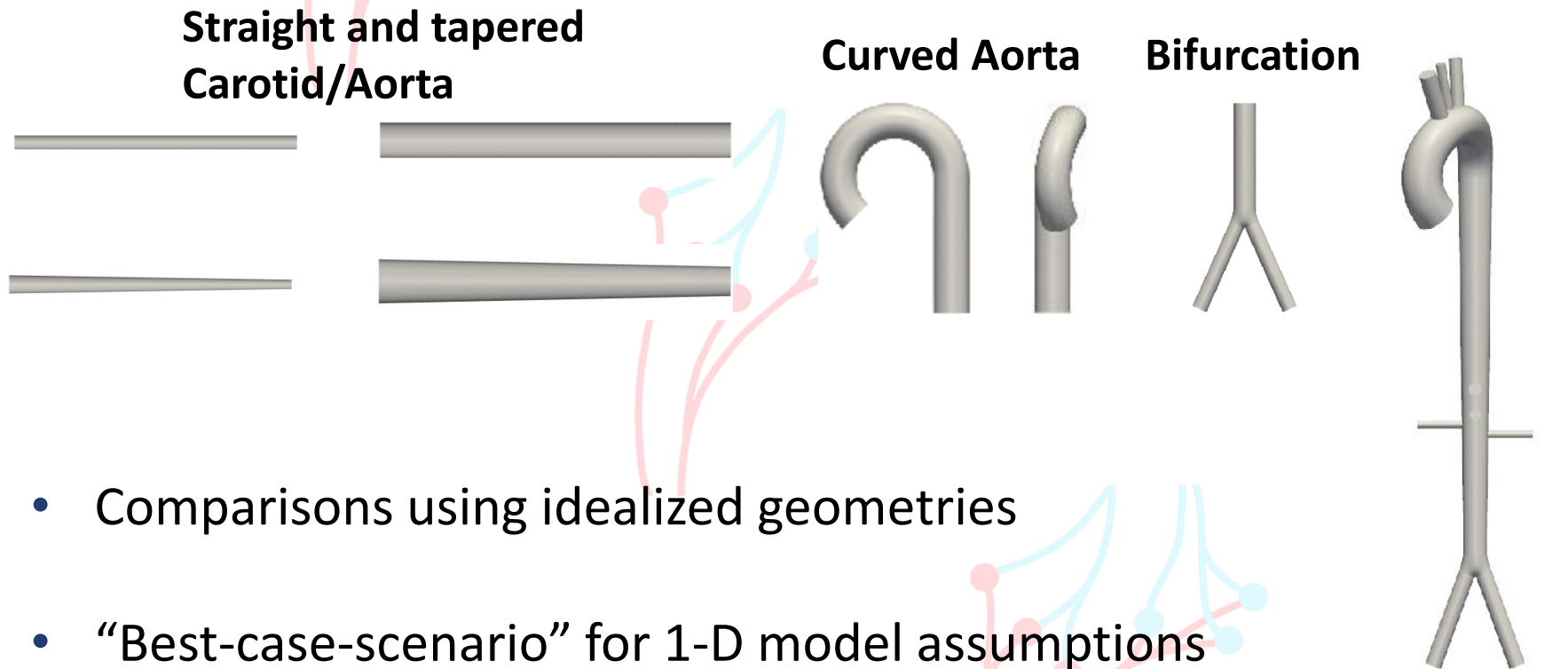
$$C_T^{n+1} = C_T^n - \frac{Q_{max} - Q_{min}}{(P_{pulse}^n)^2} \Delta t \Delta P_{pulse}^n$$

Target pulse pressure

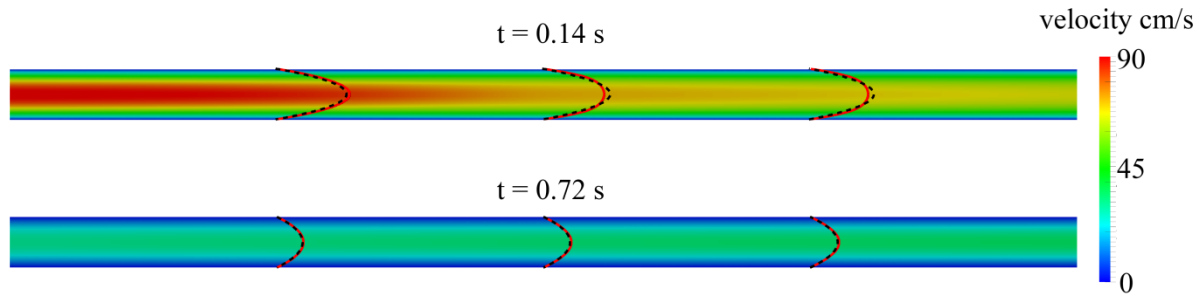
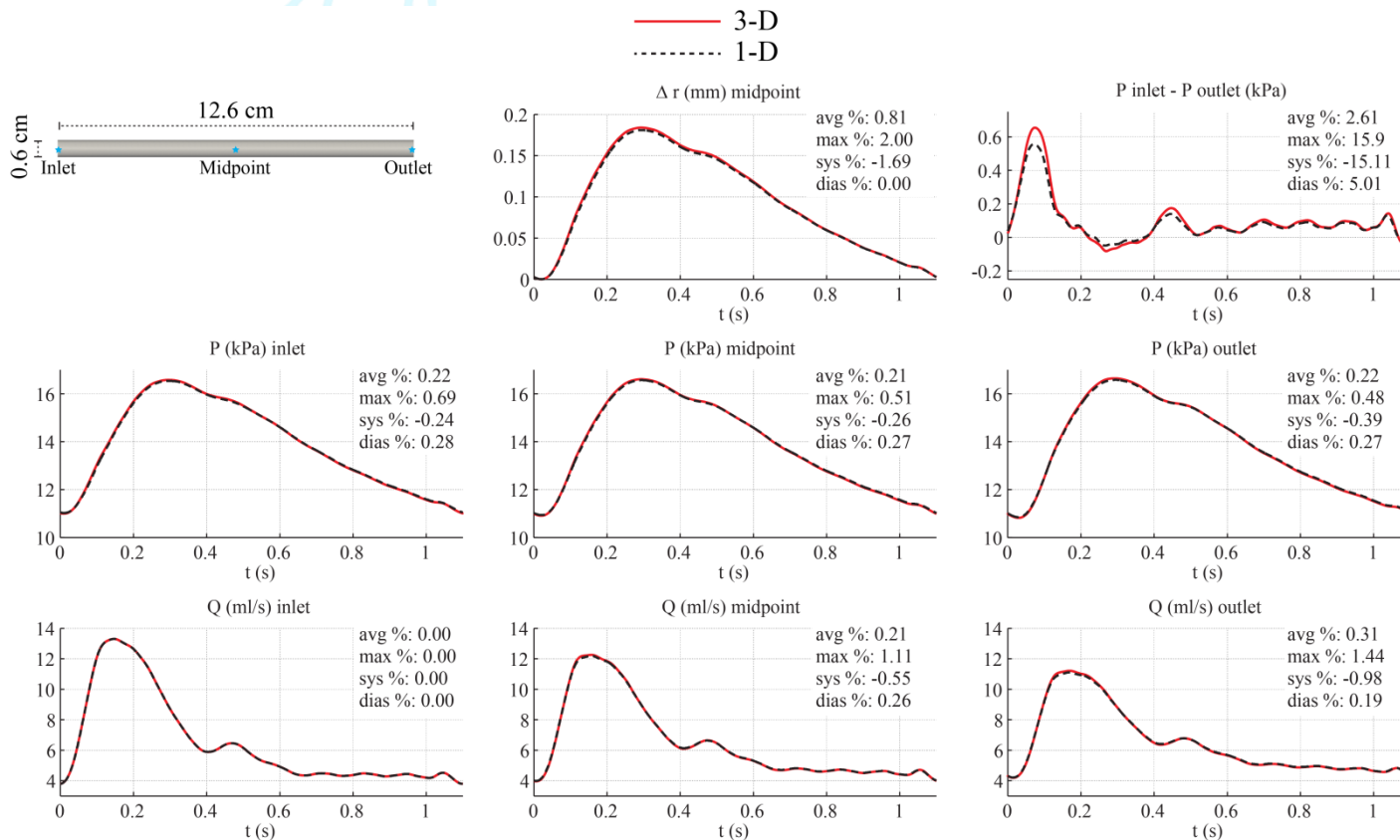
$$\Delta P_{pulse}^n = P_{pulse} - P_{pulse}^n$$

Pulse pressure after the n th 1-D simulation

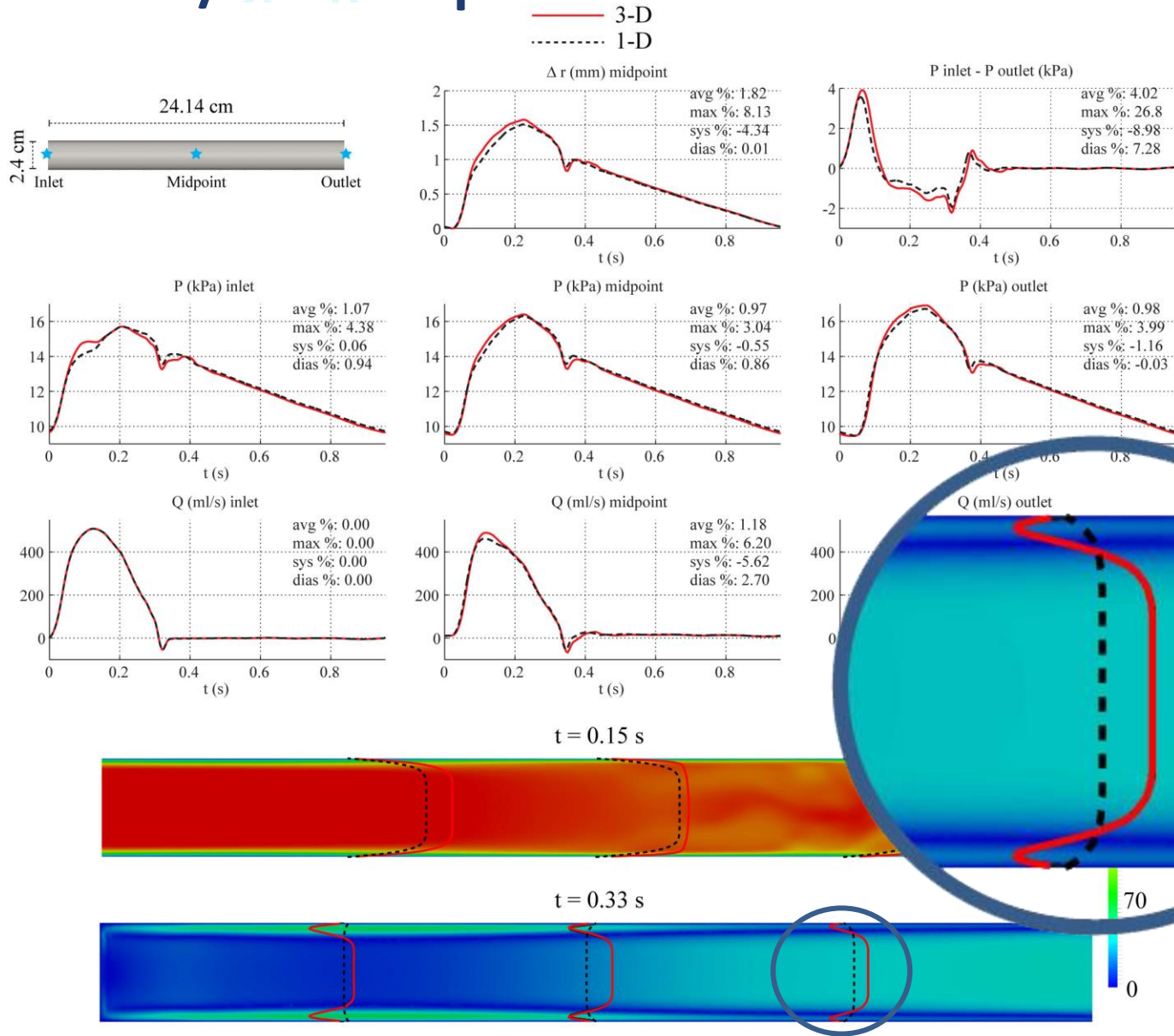
1D/3D Comparison: Idealized Geometries



1-D/3-D Comparison: Idealized Carotid

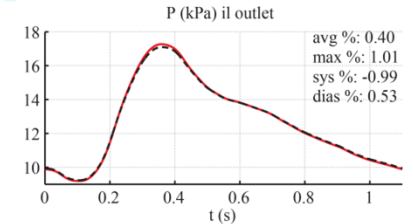
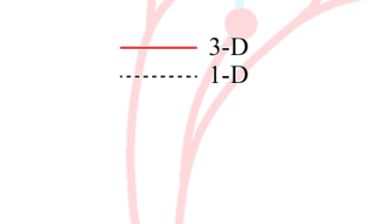
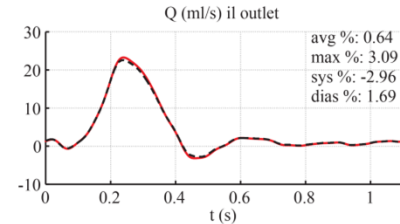
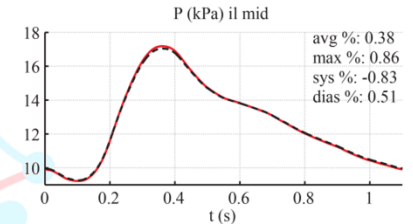
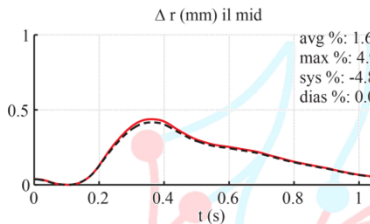
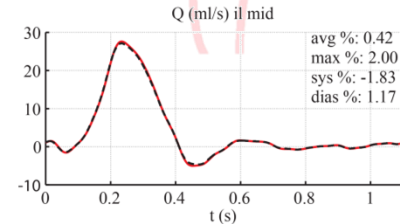
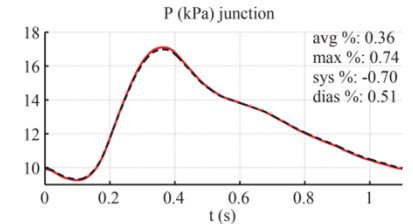
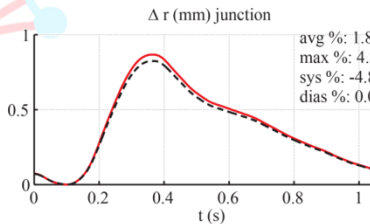
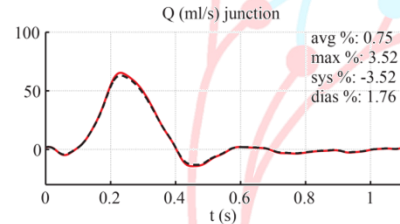
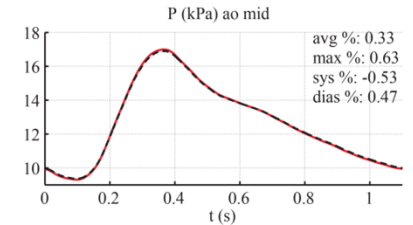
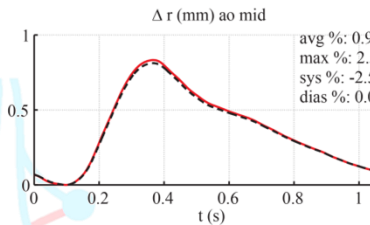
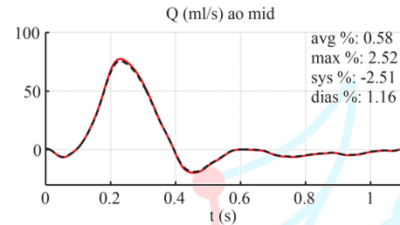
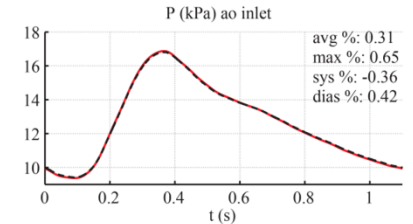
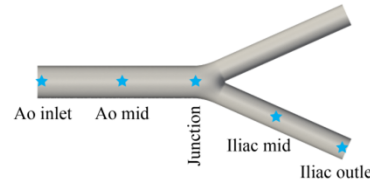
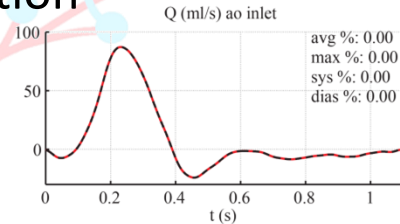
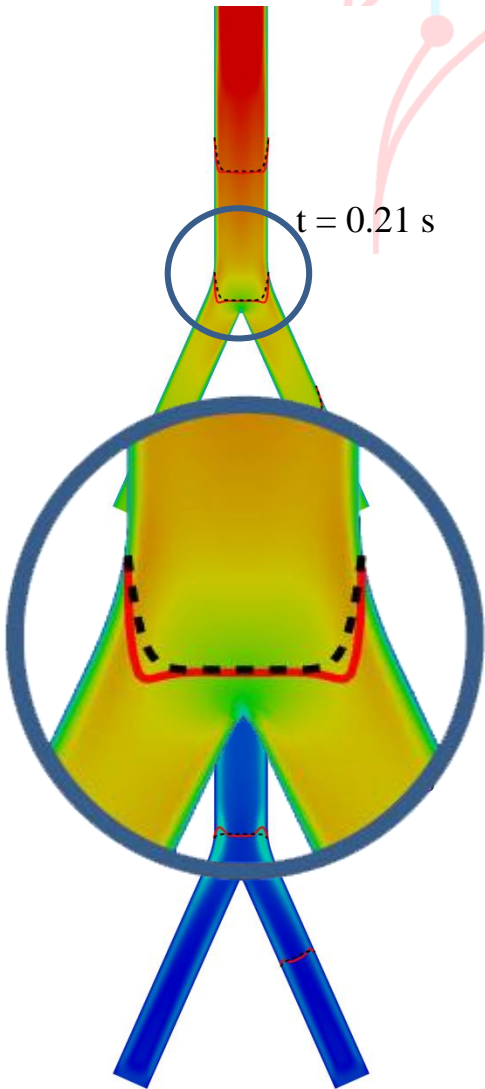


1-D/3-D Comparison: Idealized Aorta



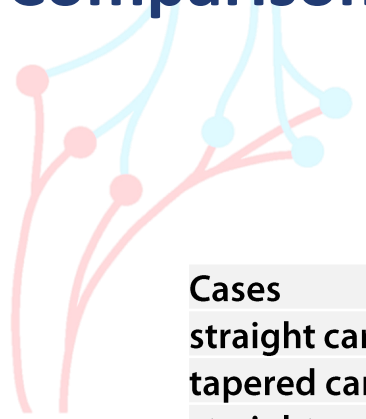
1-D/3-D Comparison: Idealized Bifurcation

Idealized aortic bifurcation



© C. Alberto Figueroa – figueroc@med.umich.edu

1D/3D Comparison: % Errors in Flow and Pressure



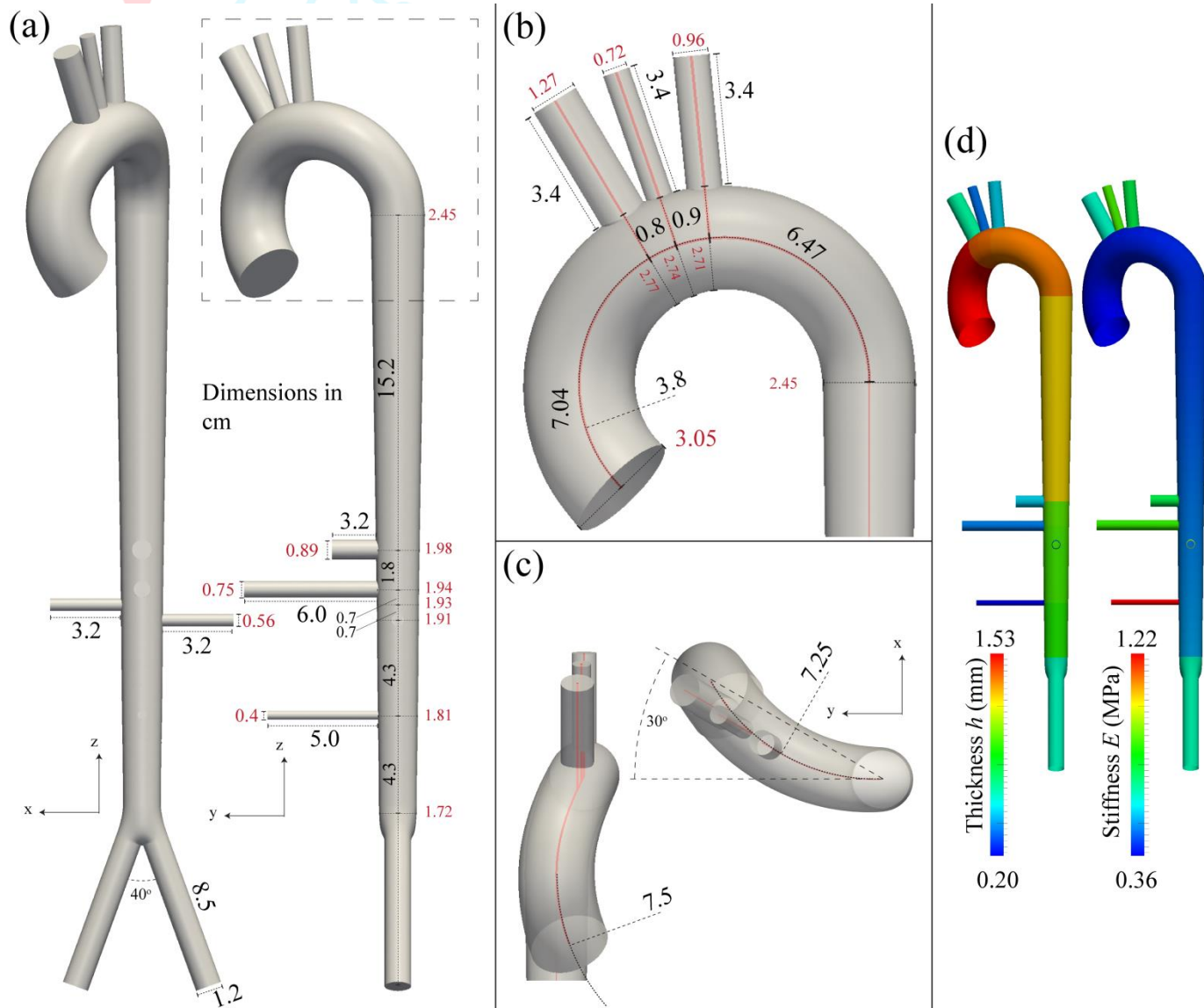
Cases	Flow	Pressure
straight carotid	0.31	0.22
tapered carotid	0.38	0.34
straight aorta	1.74	0.98
tapered aorta	1.9	1.22
larger diameter aorta	1.62	0.64
low-flow aorta	1.58	0.75
curved aorta (1 plane)	1.91	0.97
curved aorta (3 planes)	1.92	1
aortic bifurcation	0.64	0.4

Good agreement between 1D and 3D

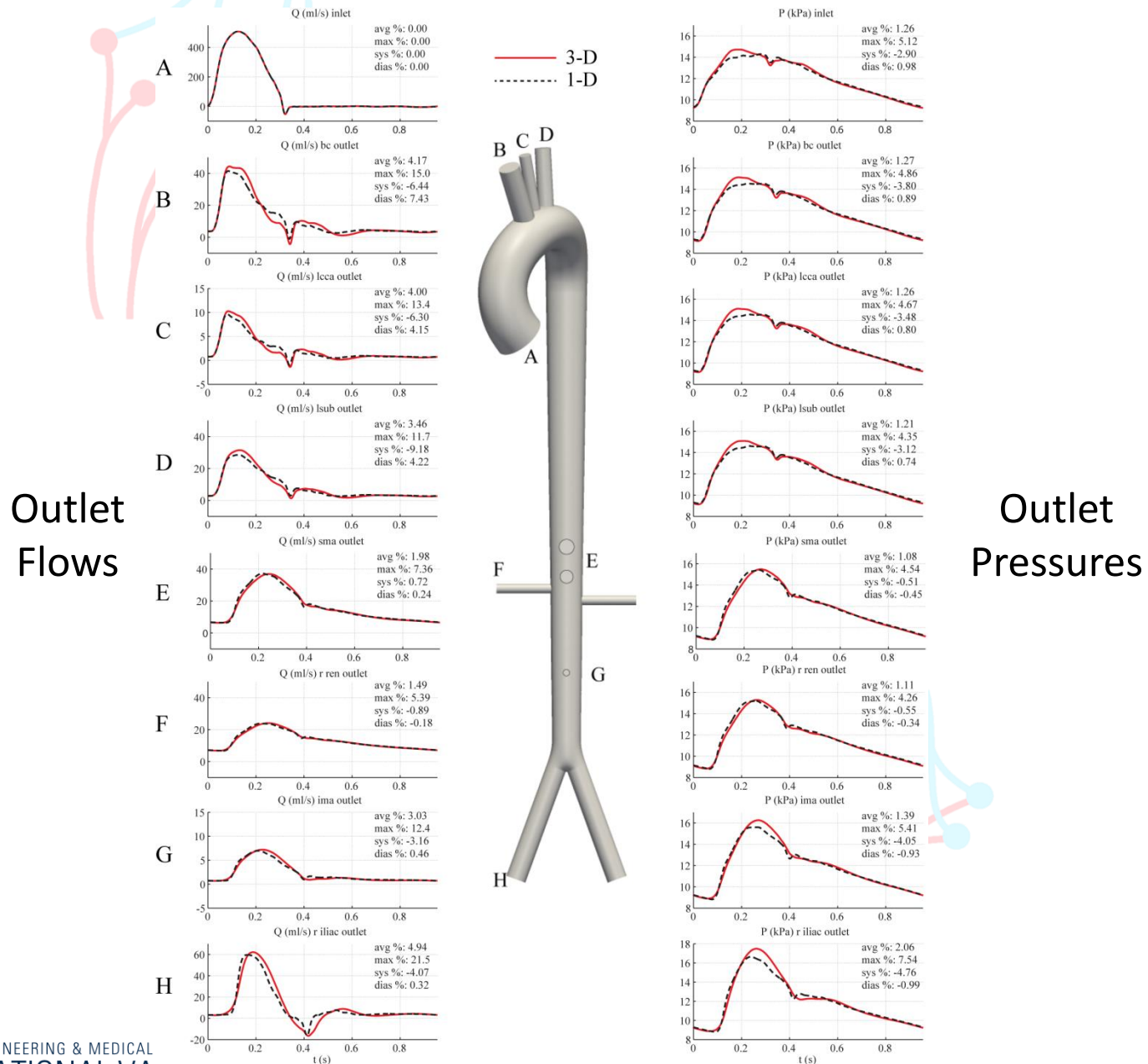
On average, relative errors less than 2% over cardiac cycle

Largest errors near peak systole

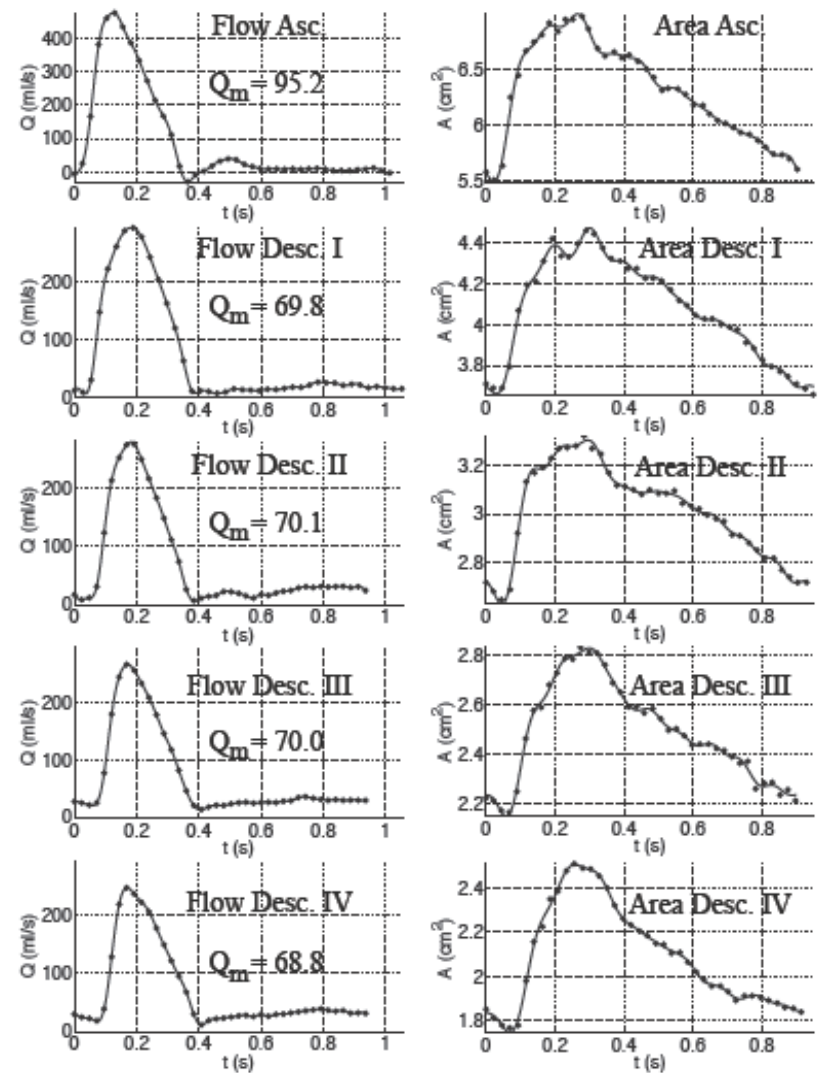
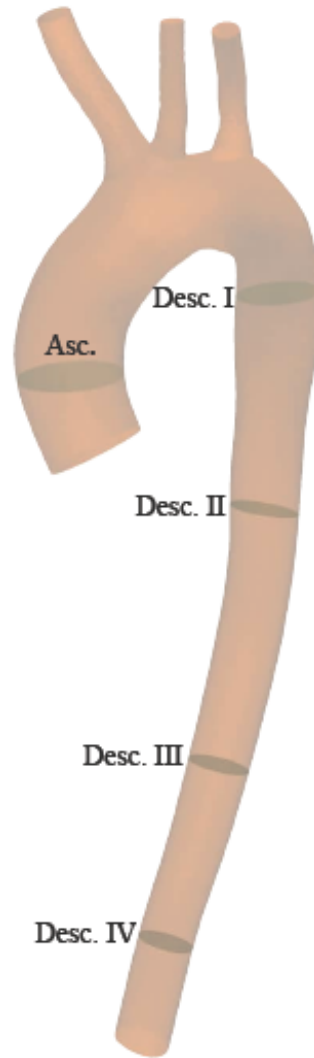
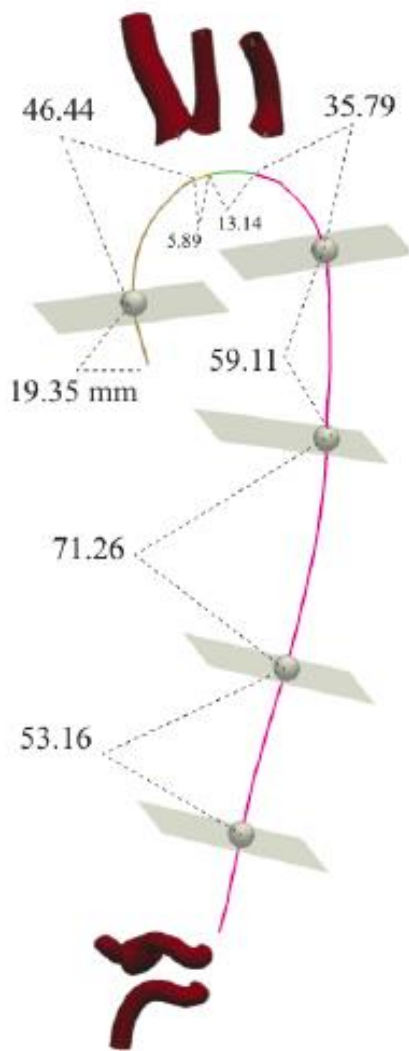
1D/3D Comparison: Idealized Full Aorta



1D/3D Comparison: Idealized Full Aorta



1D/3D Comparison: Patient-Specific Aorta



Alastruey, Xiao, Schaeffter, Figueroa, In preparation

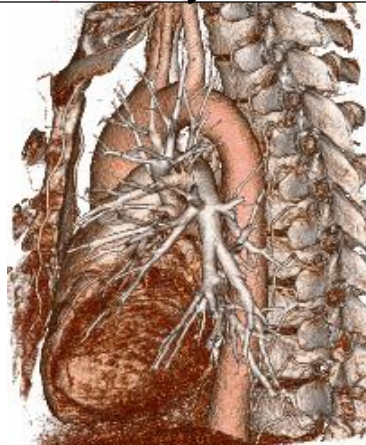
So far it's all been outflow BCs... What about the wall?

Methods for Non-Invasive Assessment of Arterial Stiffness

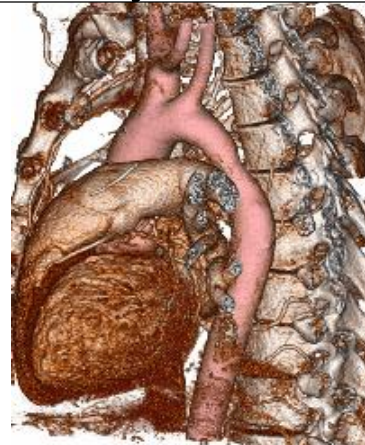
37yo male



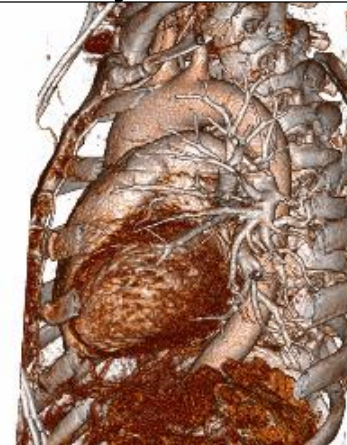
48yo male



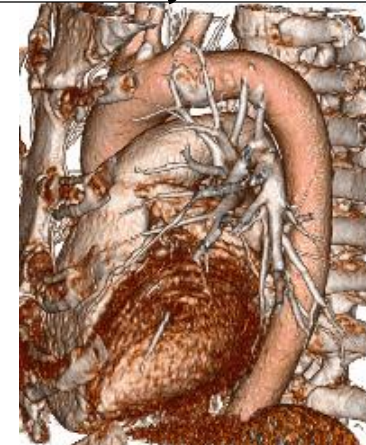
49yo male



55yo female



68yo male



Healthy aorta



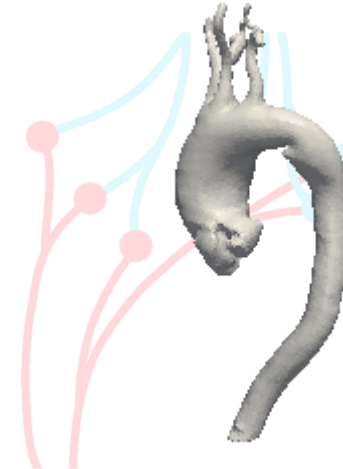
Aneurysmal dilatation of the ascending aorta.



Aneurysmal dilatation of the aortic root. Repaired coarctation



Aneurysmal dilatation of the ascending aorta



Calcification of the transverse aortic wall

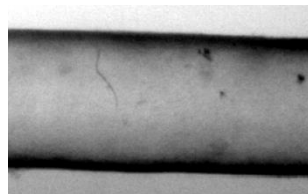
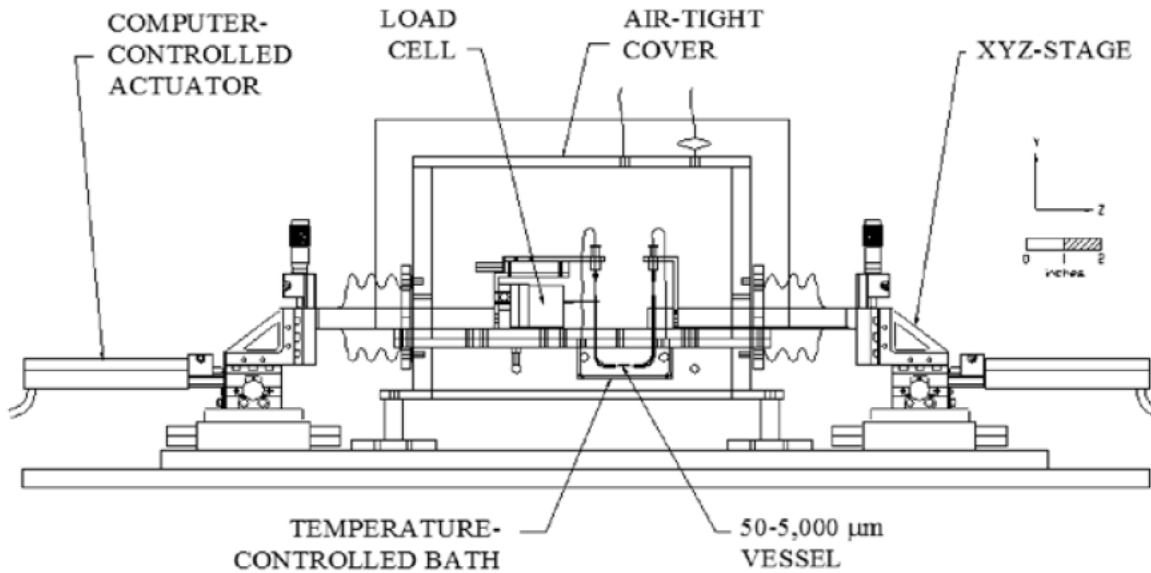


© C. Alberto Figueroa

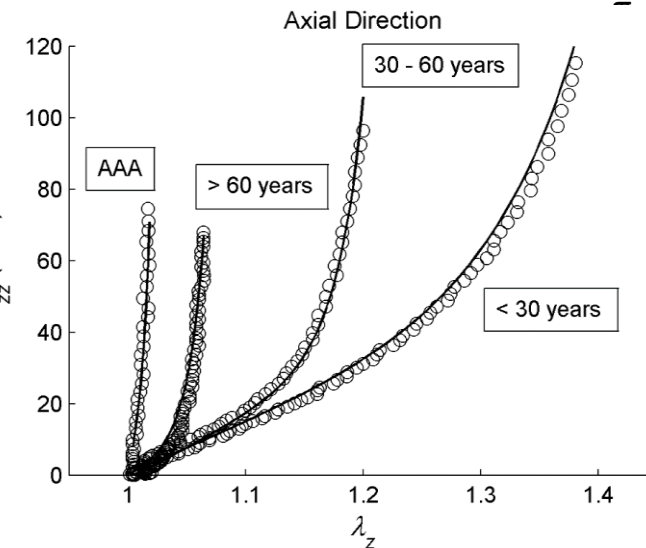
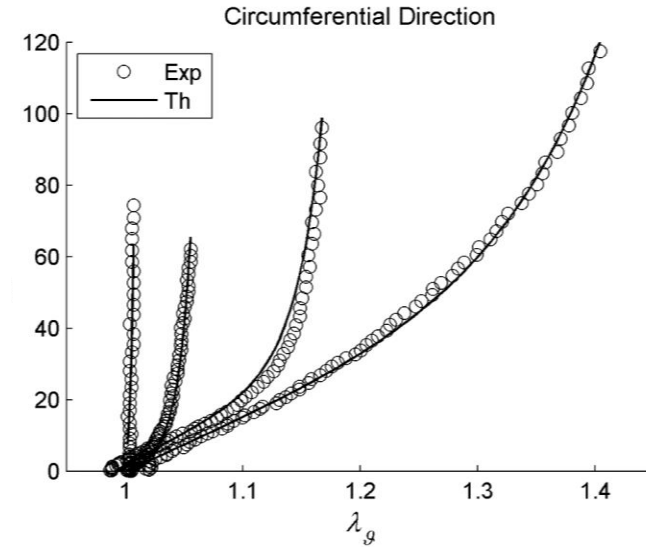


Methods: Image-based Modeling of Hemodynamics

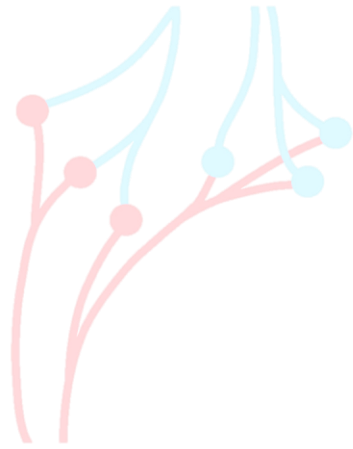
Methods for Invasive Assessment of Arterial Stiffness



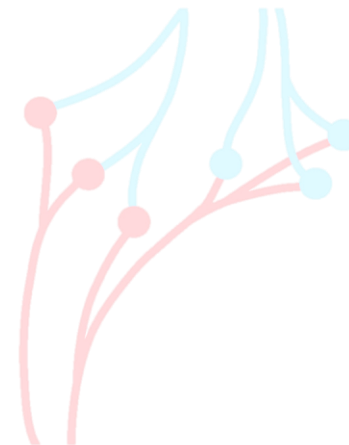
Gleason et al., J Biomech Eng 2004

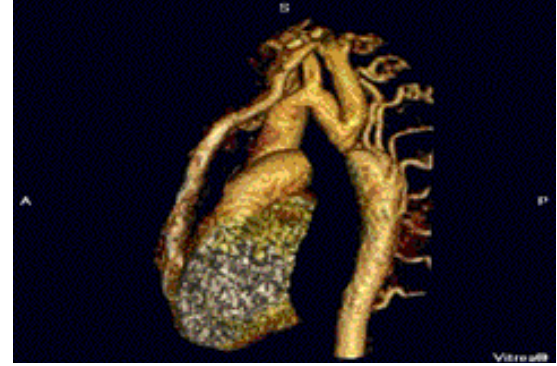


Ferruzzi et al., J Roy Soc Inter 2010



Case study: Pressure Gradients in Aortic Coarctation

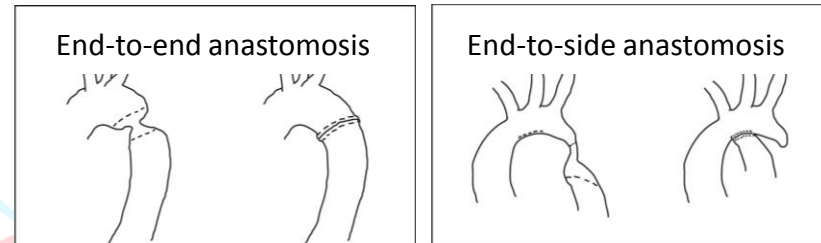




tu

• Aortic Coarctation (CoA)

- 8%-11% of congenital heart defects (10 000 patients annually in Western world)
- Treatment: alleviate blood pressure (BP) gradient through the coarctation
- Open repair or stenting

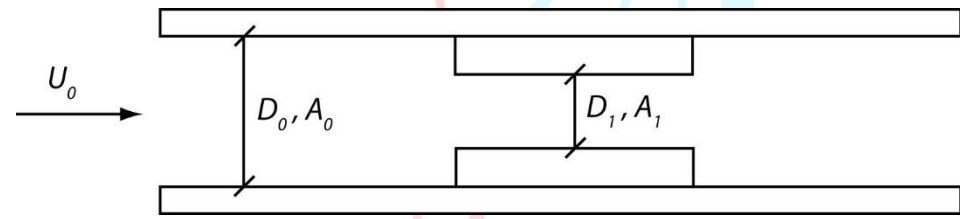


• Diagnosis and treatment planning: importance of BP metrics:

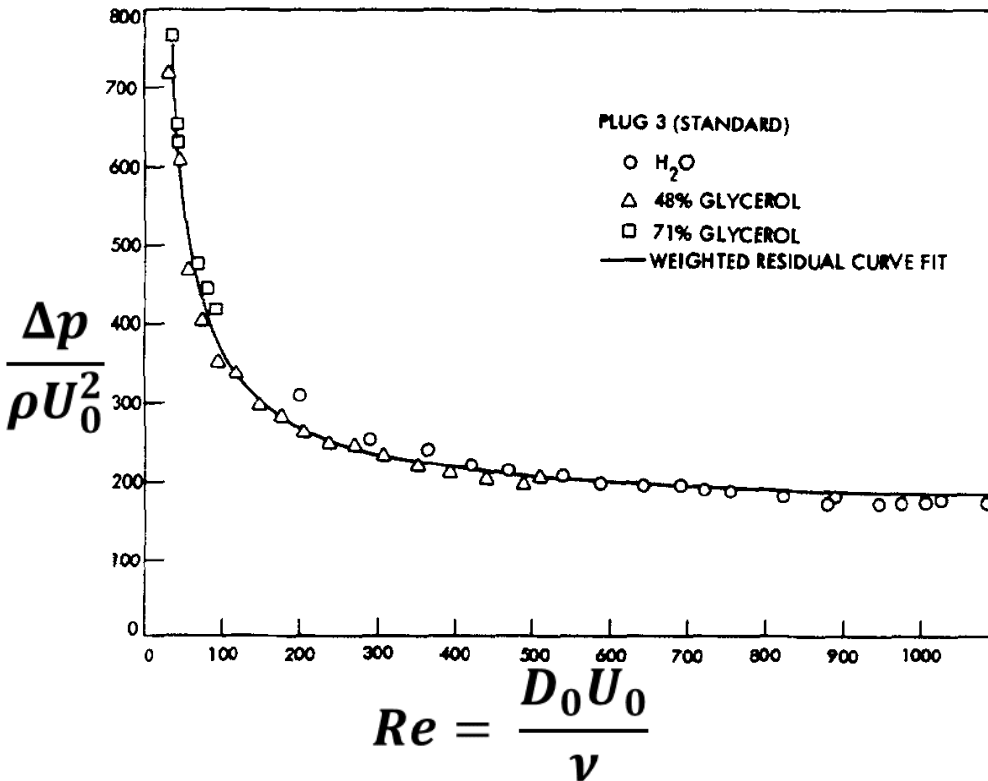
- BP at rest:
 - Catheter-driven transducer (accurate but **invasive**)
 - Sphygmometer (less accurate but non-invasive)
 - Doppler ultrasound imaging (Bernoulli's equation)
- BP at stress (pharmacologically-induced):
 - Catheter-driven transducer (accurate but **invasive**)
- Current putative treatment guideline: **BP gradient > 20 mmHg at rest**

© C. Alberto Figueroa – figi

Pressure gradient (drop) through a stenosis



Seeley & Young, J Biomech, 1976



U_0 : mean velocity unobstructed tube

D_0, A_0 : Diameter/Area unobstructed tube

D_1, A_1 : Diameter/Area obstructed tube

Reynolds number:

$$Re = \frac{D_0 U_0}{\nu}$$

ν : fluid viscosity

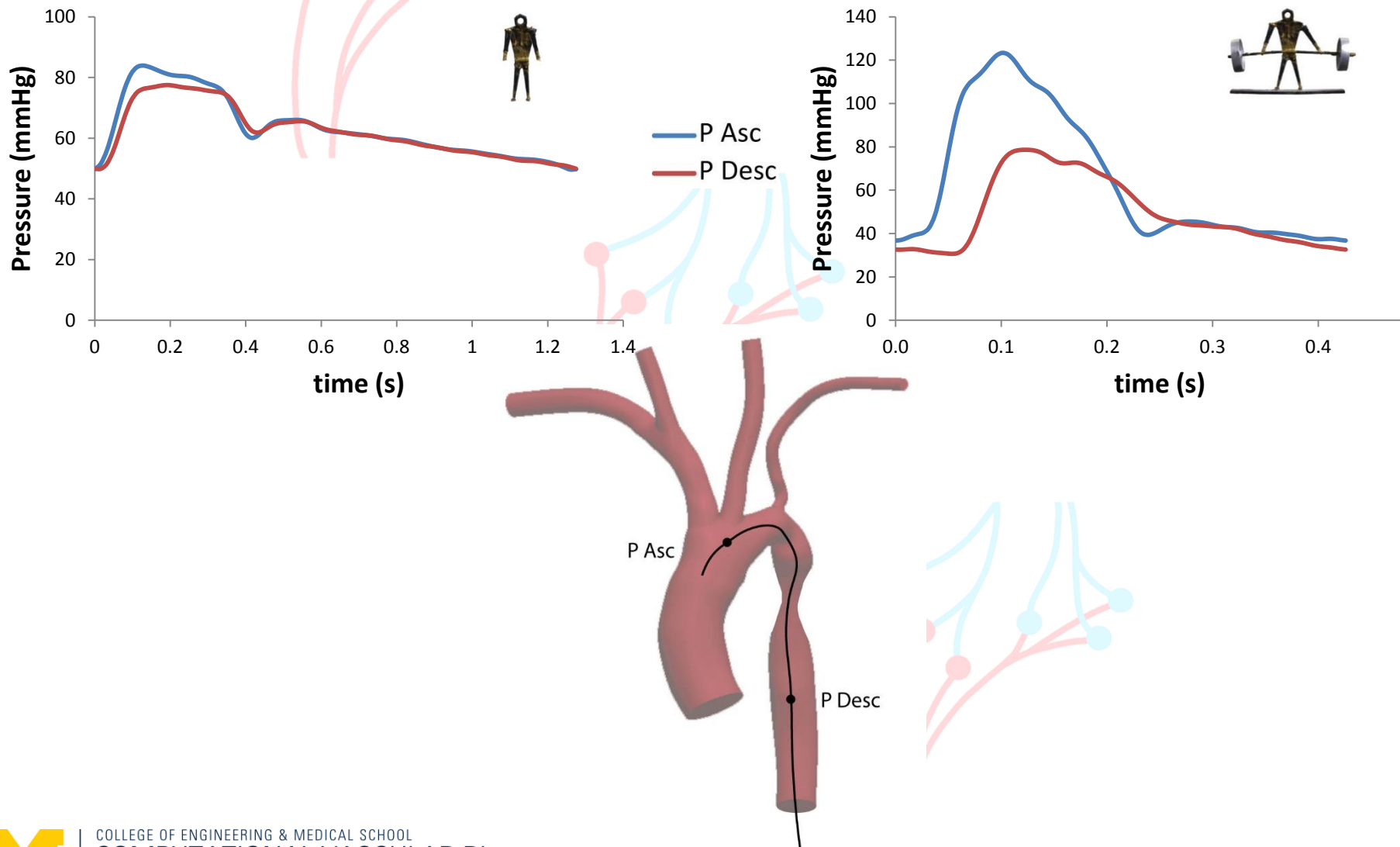
For medium-large Re ,

$$\Delta p \sim \text{constant} \cdot \rho U_0^2 \sim \text{constant} \cdot Q_0^2$$

Pressure gradient has a complex, nonlinear dependency on flow

Pressure gradient (drop) through a coarctation

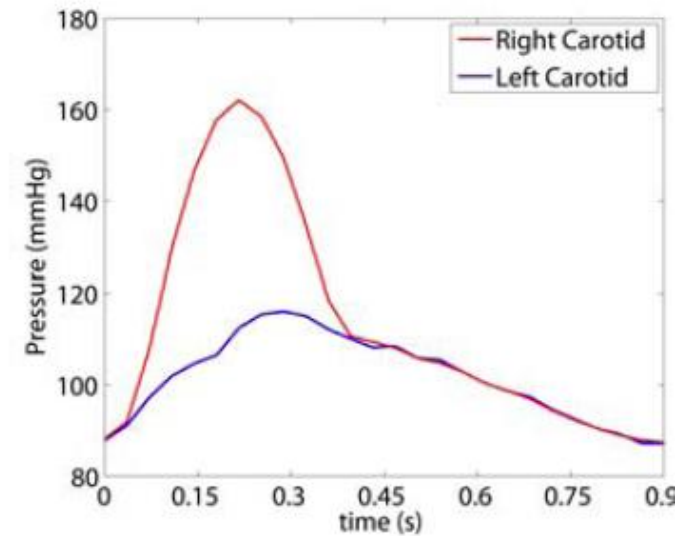
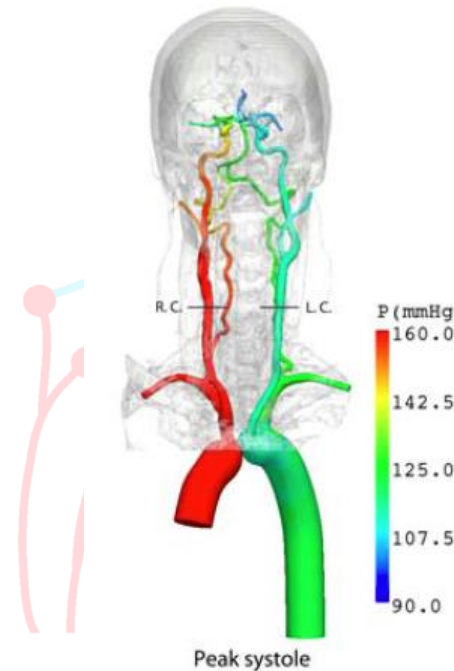
- Pressure wire measurements at rest and stress



© C. Alberto Figueroa - figueroa@med.umich.edu

Implications of abnormal pressure indices

- Lessons learned from animals models of hypertension



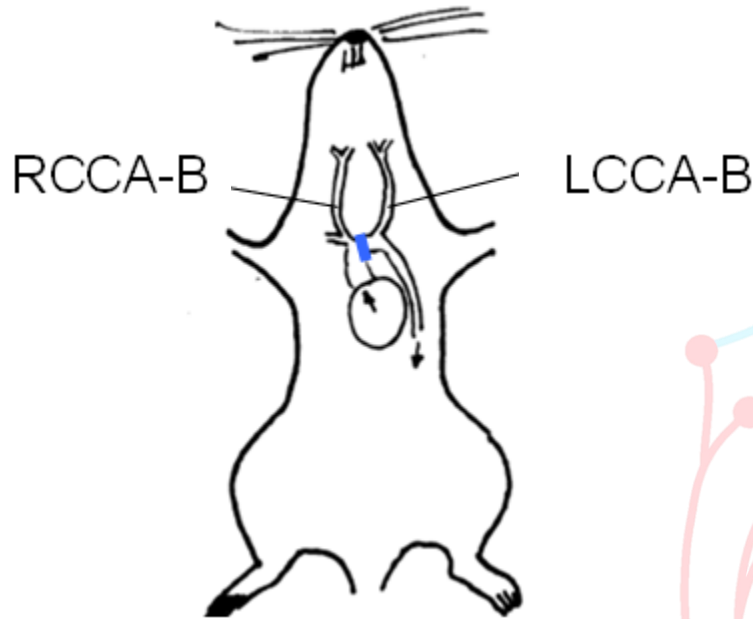
Li et al., Ultrasound in Med and Biol 2003

Coogan, Humphrey, Figueroa, Biomed & Model Mechanob 2013

- Transverse **aortic banding** revealed that **vessel remodeling (thickening and stiffening)** is strongly correlated with changes in **pressure pulse**
- Short time-courses also showed **marked changes in vascular structure**

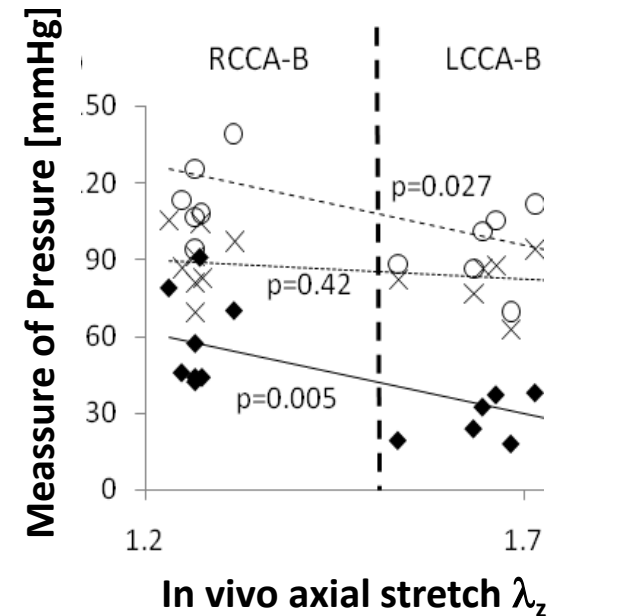
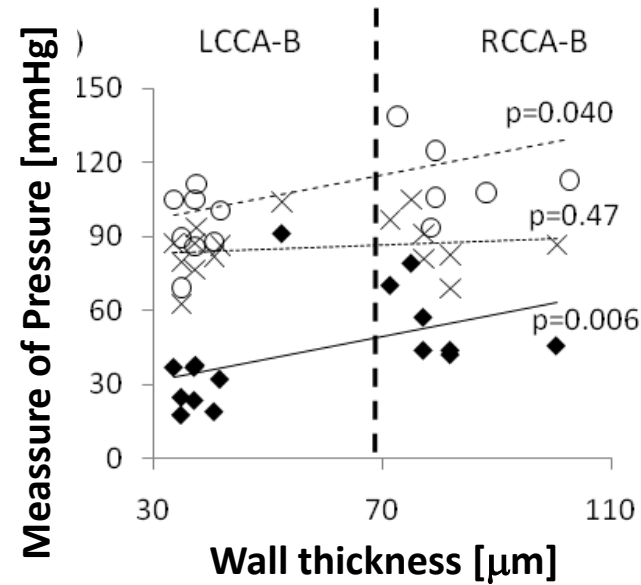
© C. Alberto I

Implications of abnormal pressure indices



Eberth et al., J Hypertens 2009

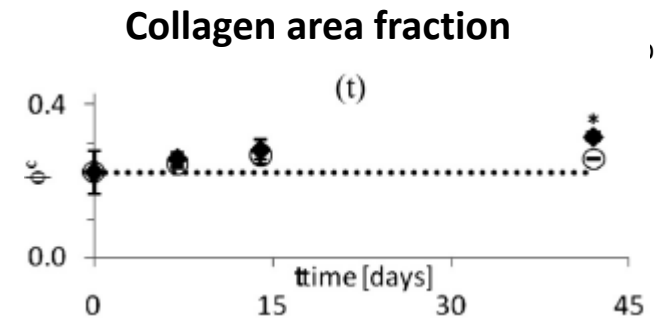
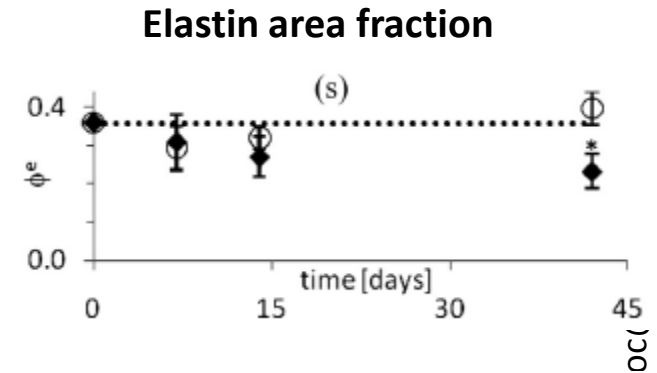
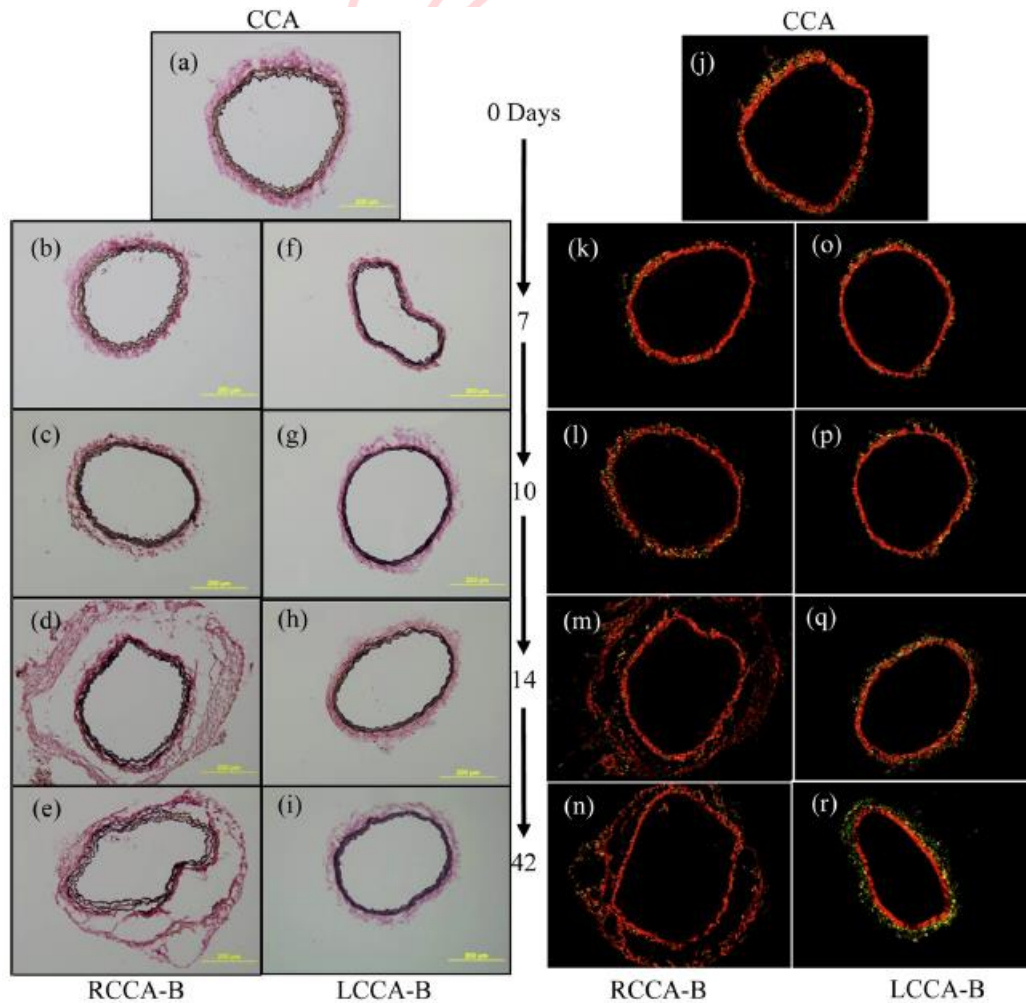
- **Pulse pressure** is associated with **wall thickening**
- **Pulse pressure** is associated with **loss of axial stretch**



× Mean
○ Syst.
◆ Pulse

Implications of abnormal pressure indices

- **Pulse pressure** is associated with **loss of elastin and collagen production**.



◆ RCCA-B

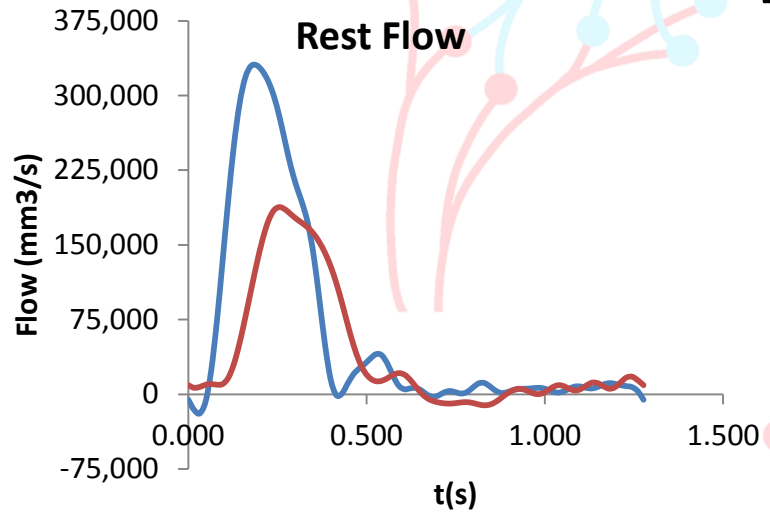
○ LCCA-B

Eberth et al.,
Am J Physiol Heart Circ Physiol 2010

© C. Alt

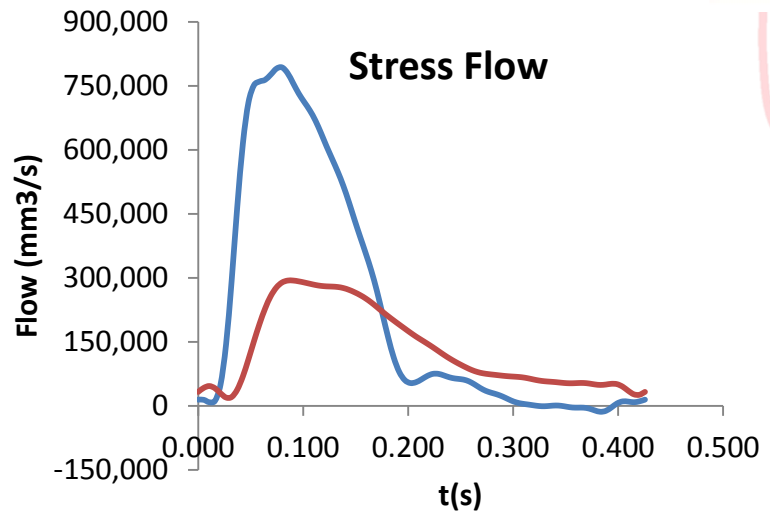
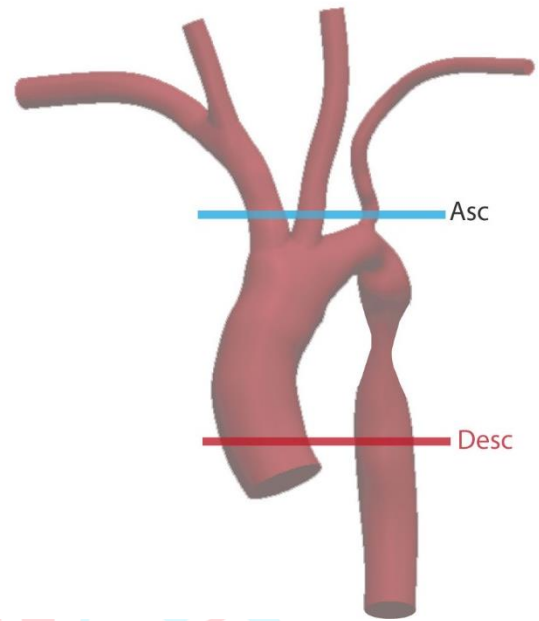
CMR & pressure data in repair CoA patients at rest & stress

2D PC-MRI data



	AscAo	Innominate	LCC	LS	DiaphAo
Total Flow (L/min)	3.71	0.624	0.312	0.364	2.41
% AscAo	100	17	8	10	65

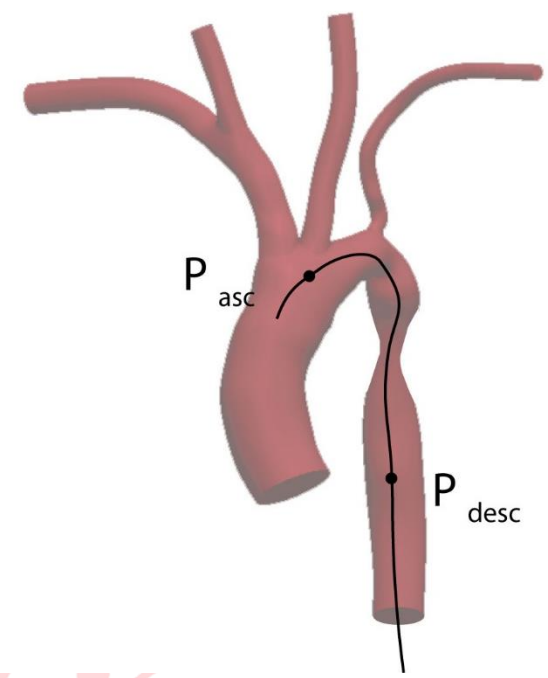
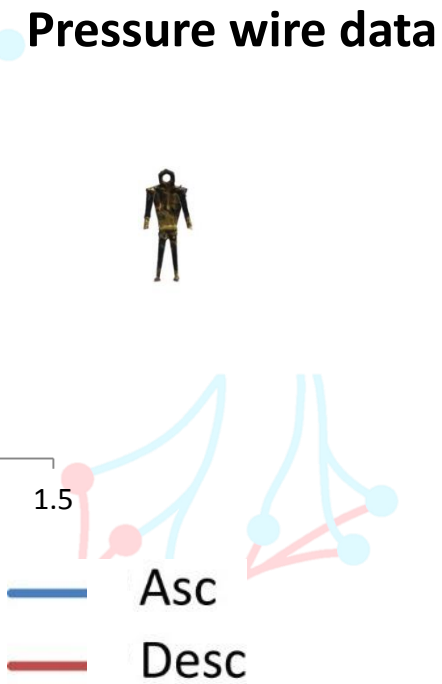
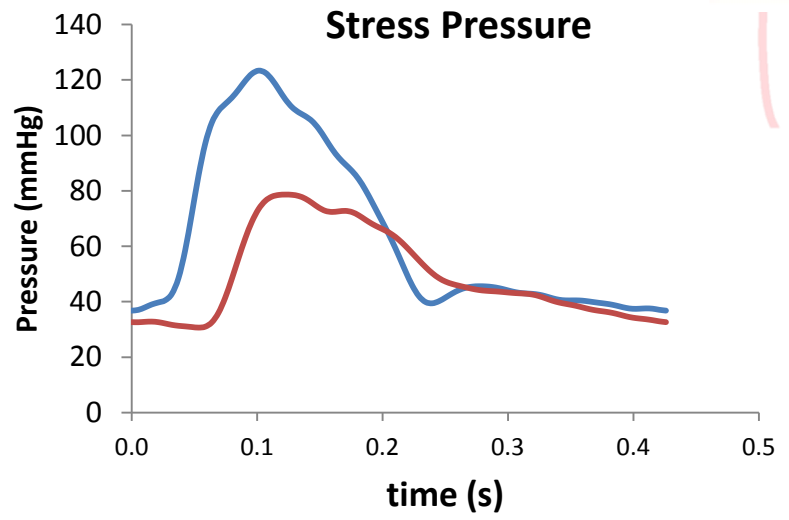
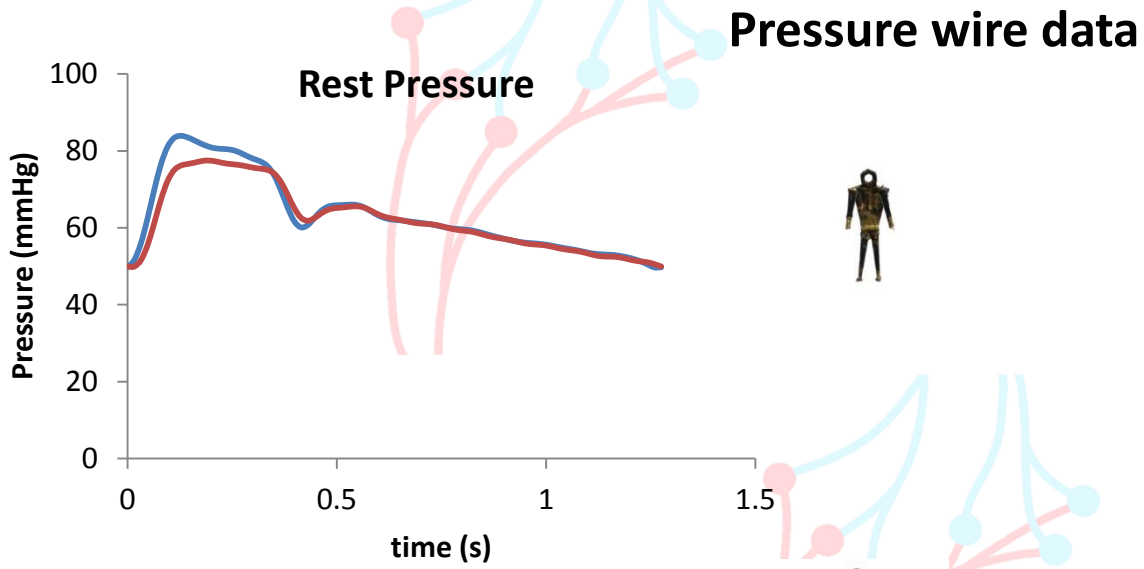
— Asc
— Desc



	AscAo	Innominate	LCC	LS	DiaphAo
Total Flow (L/min)	13.53	3.38	0.68	1.49	7.98
% AscAo	100	25	5	11	59

© C. Alberto Figueroa – figueroc@med.umich.edu

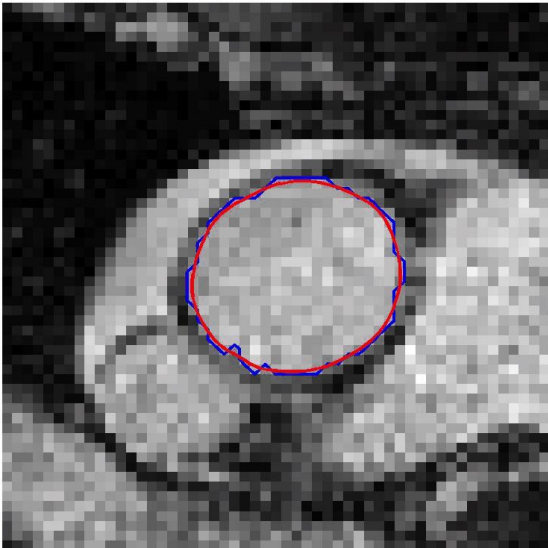
CMR & pressure data in repair CoA patients at rest & stress



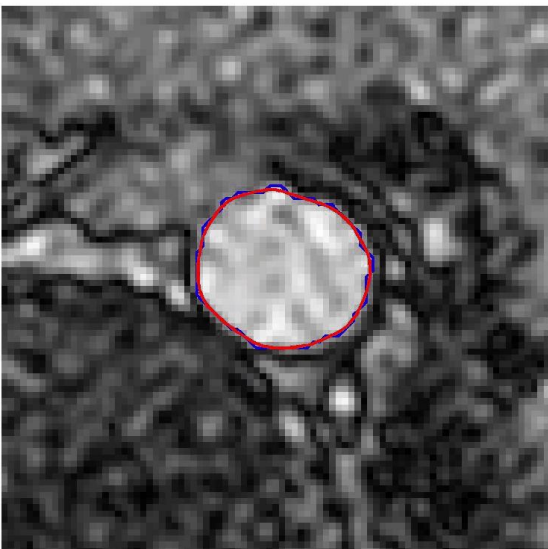
CMR & pressure data in repair CoA patients at rest & stress



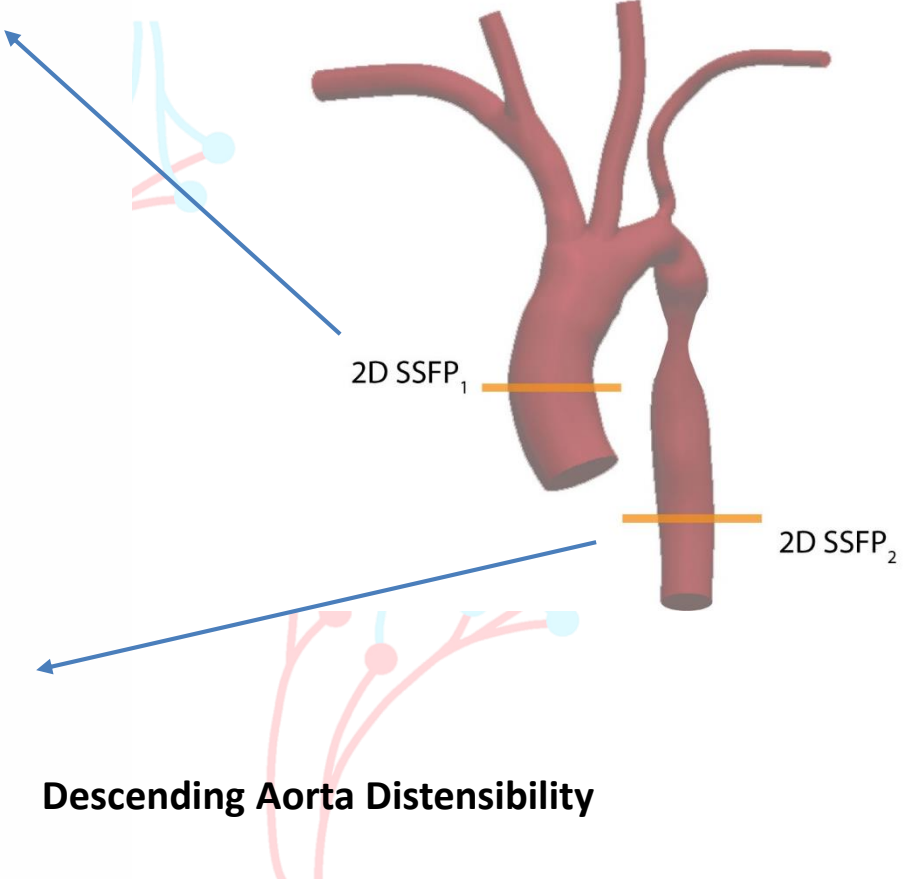
2D-SSFP data



Ascending Aorta Distensibility

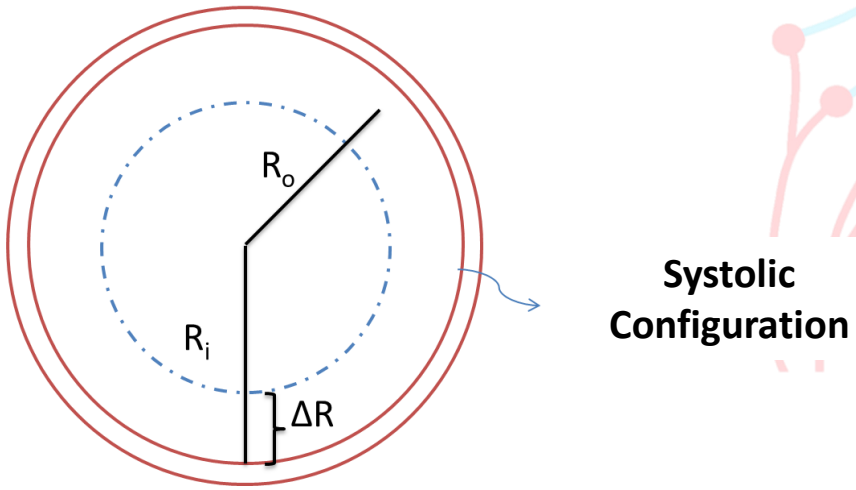
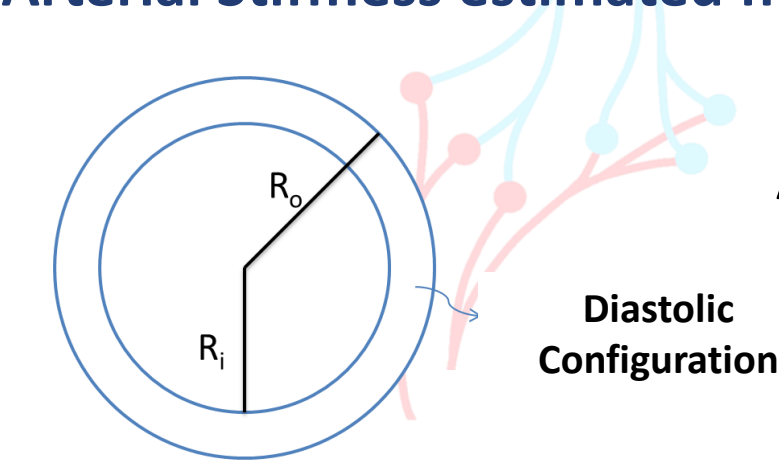


Descending Aorta Distensibility

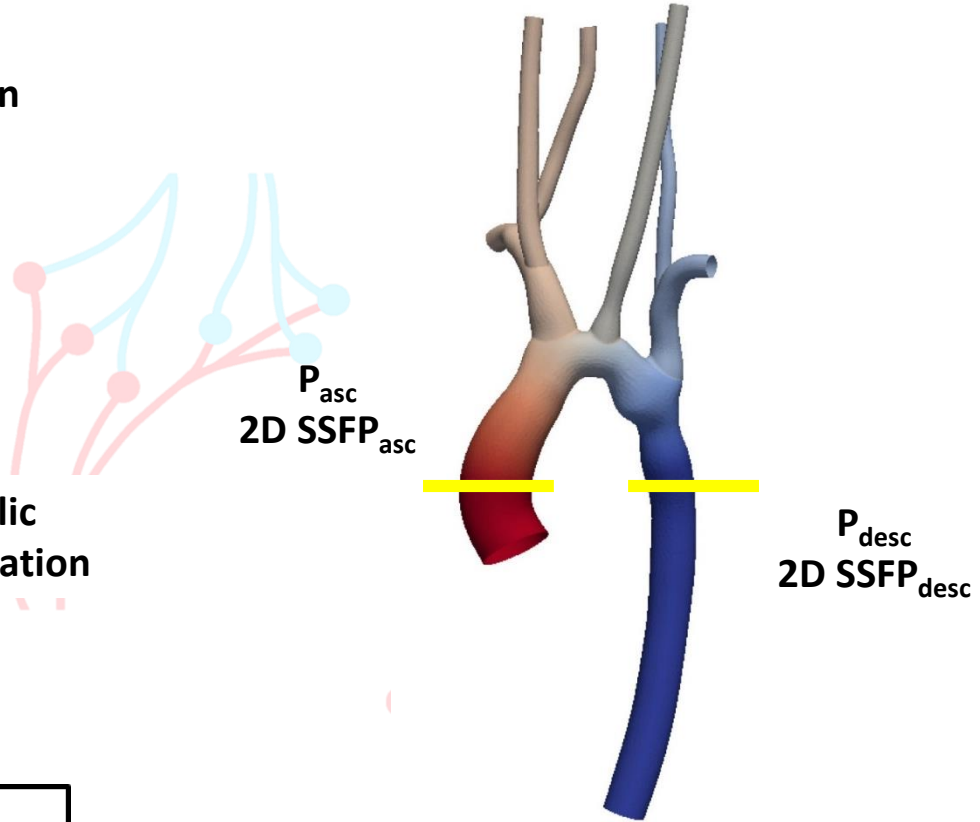


Arterial Stiffness estimated from Pressure and Vessel Motion

Simultaneous knowledge of distensibility AND pressure is used to derived elastic properties



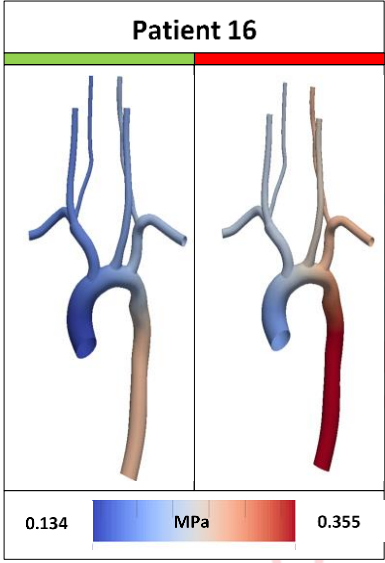
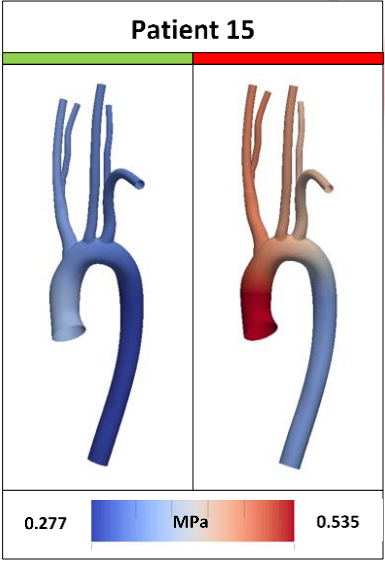
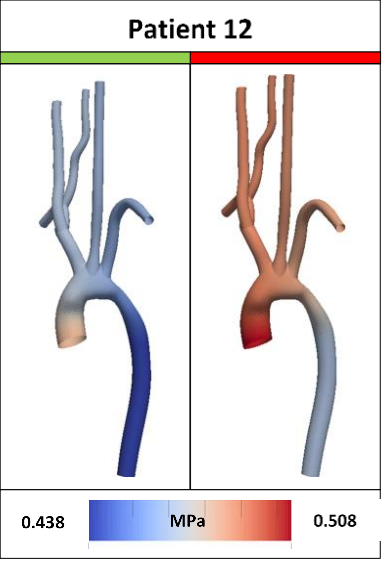
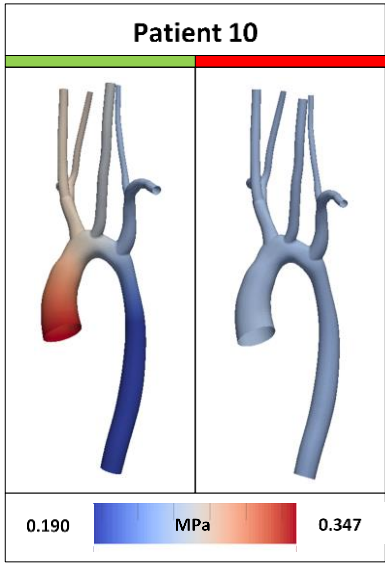
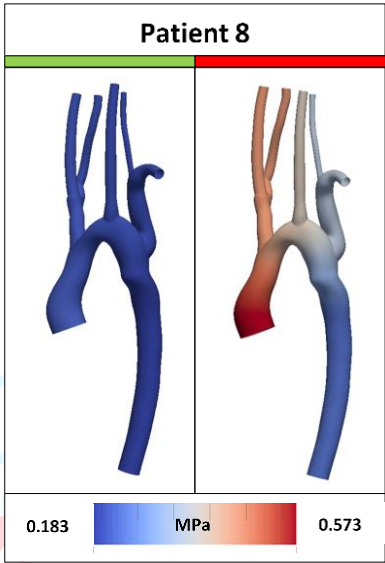
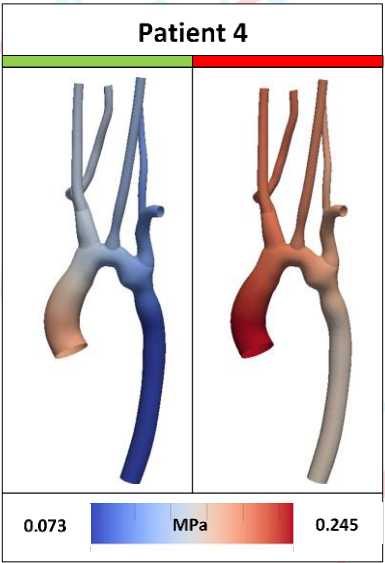
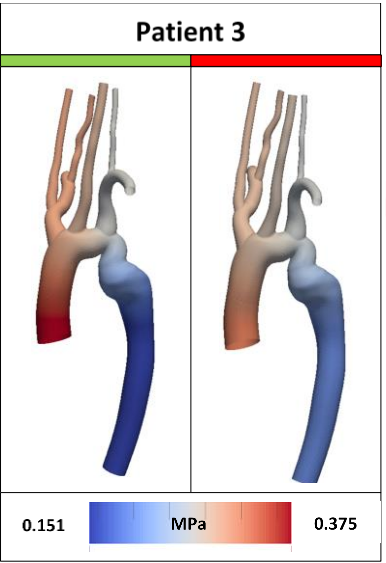
$$E = \frac{1.5 \cdot \Delta P \cdot R_i^2 \cdot R_o}{(R_o^2 - R_i^2) \Delta R}$$



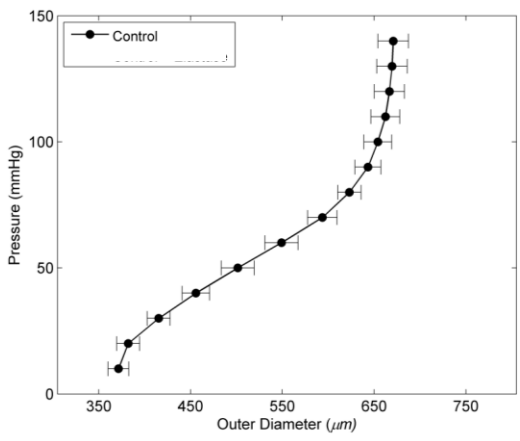
© C. Alberto Figueroa – figueroc@med.umich.edu

Arterial Stiffness in repaired CoA patients at rest & stress

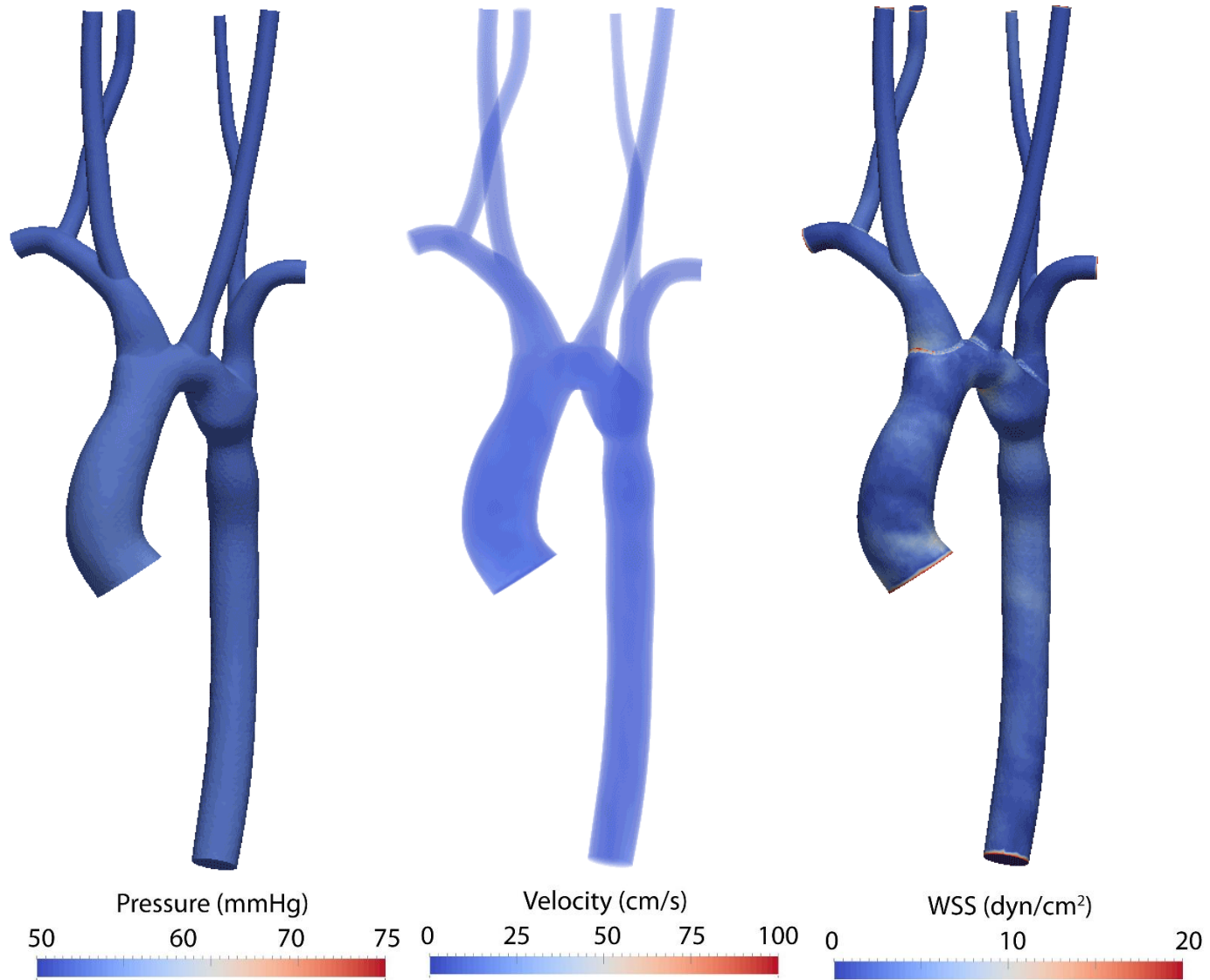
Vessel stiffness increases with stress (pressure)



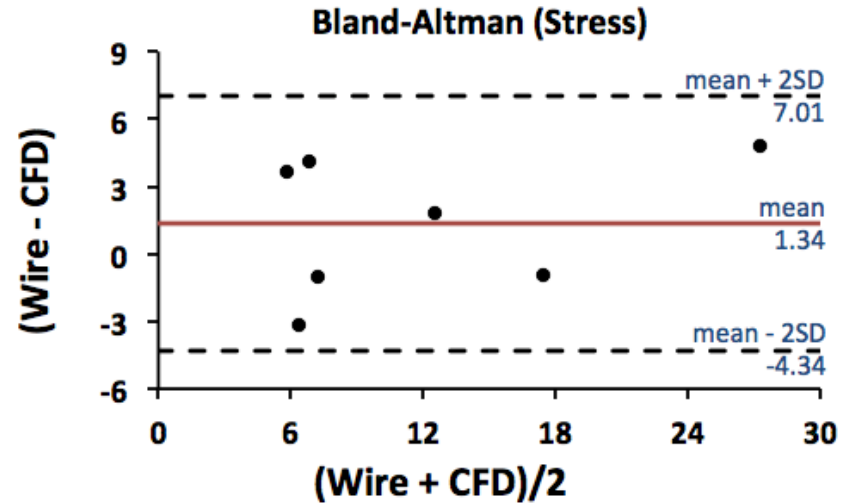
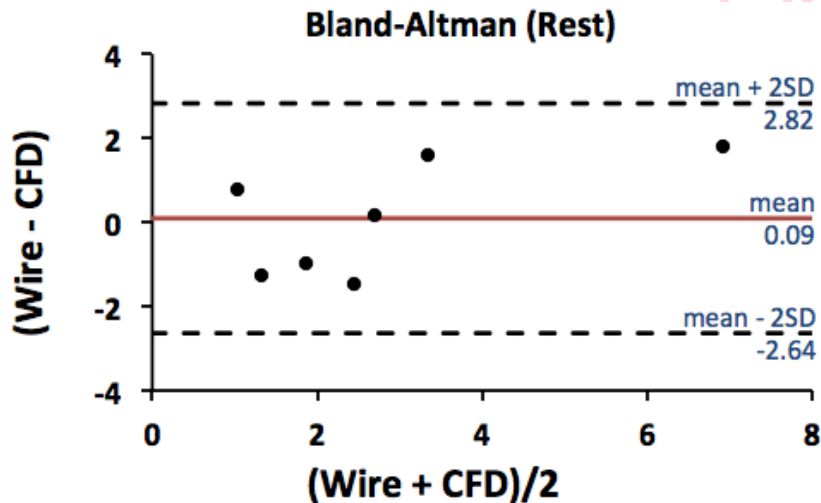
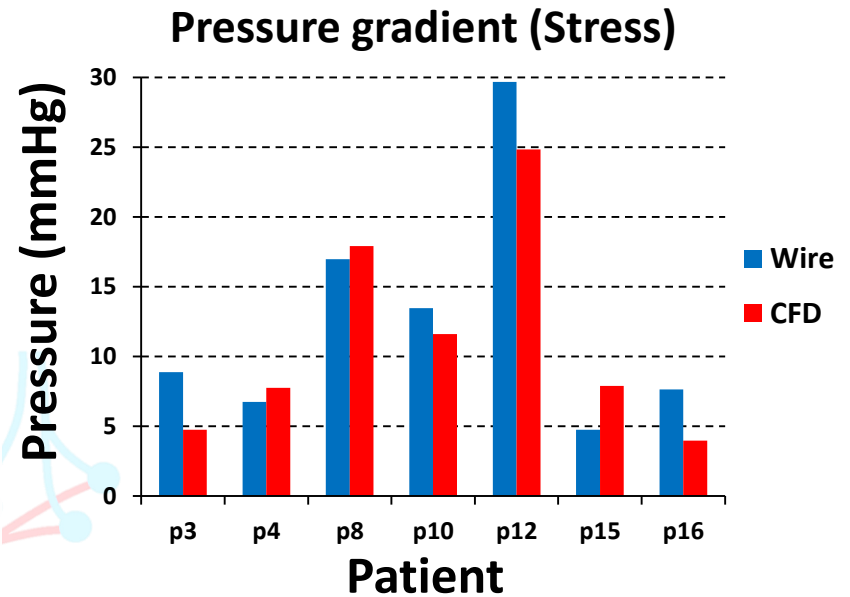
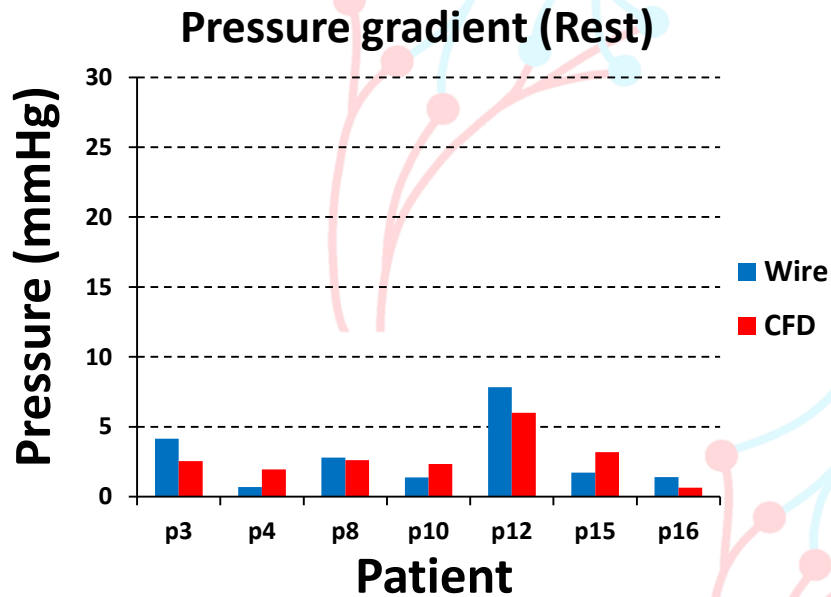
Rest
Stress

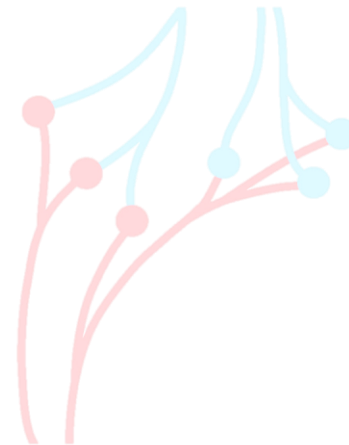
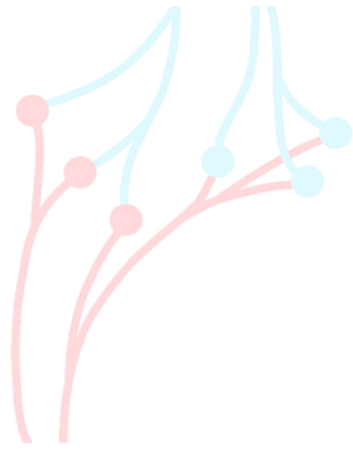


Results – CFD predictions



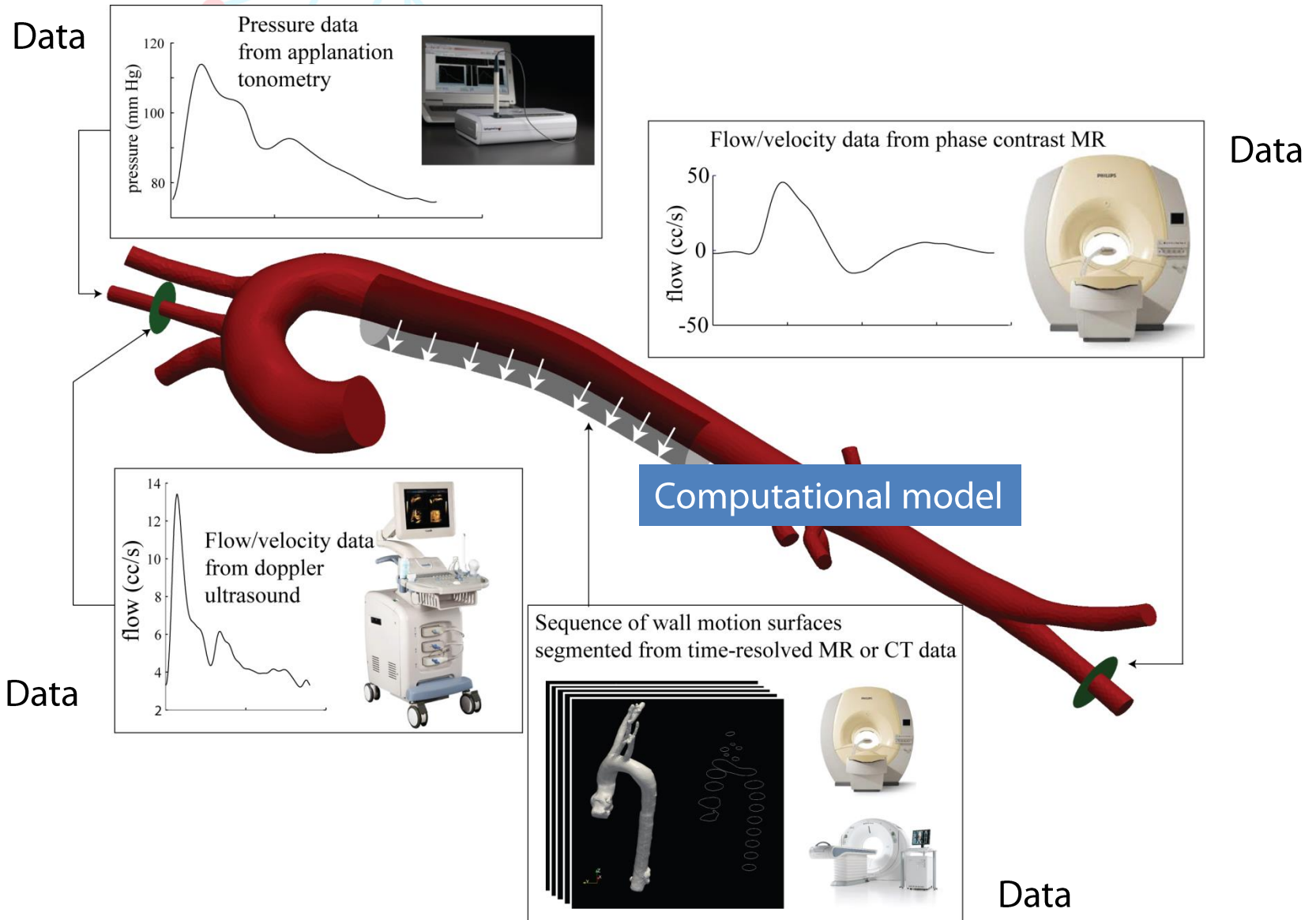
Validation of computational predictions





Filtering Techniques for Parameter Estimation

3D Data Assimilation Framework



Data Assimilation Framework

- Data assimilation: combine mathematical model with real-world measurements to produce estimate of “true state” of system (including the values of the model parameters)
- We adopted a sequential approach based on a reduced order unscented Kalman filter^{1,2,3}
- The goal of this work is to explore applications in blood flow simulation in systemic arterial networks

1. Moireau et al. *ESAIM: Control, Optimisation and Calculus of Variations*. 2010
2. Chabiniok et al. *BMMB*. 2012
3. Bertoglio et al. *IJNMBE*. 2012

The Model and Augmented State

- The model (forward problem)

$$\dot{X} = A(X)$$

model operator
(i.e. Navier-Stokes)

state

$$X(0) = X_0 + \zeta^X$$

initial uncertainty/error

- Augmented state

$$\chi = \begin{pmatrix} X \\ \theta \end{pmatrix}$$

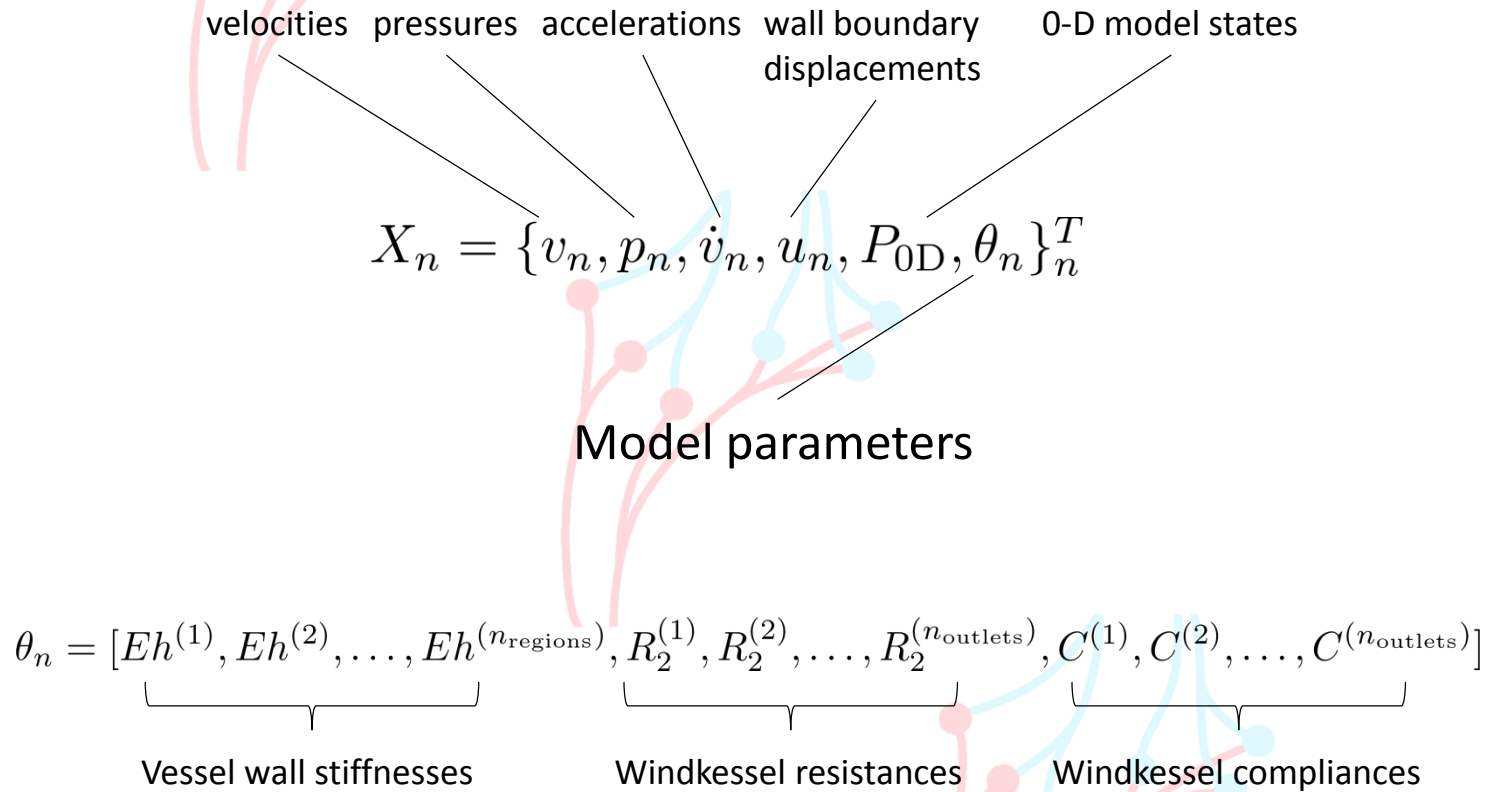
parameters

$$\dot{\chi} = \mathcal{A}(\chi)$$

$$\chi(0) = \chi_0 + \zeta^\chi$$

Includes uncertainty
in the parameters

State Variables and Parameters

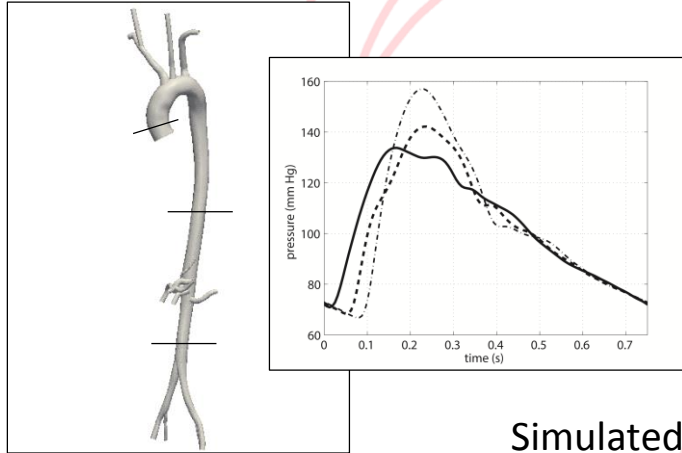


Observation Error

$$Z = H(X) + \zeta^z$$

observation operator

measurement error



Cross-sectional averaged pressure and flow

$$H(X_n) = [Q_1, Q_2, \dots, Q_{n_{\text{obs-Q}}}, P_1, P_2, \dots, P_{n_{\text{obs-P}}}]^T,$$

$$Q_i = \int_{a_i} v(x, t_n) \cdot \vec{n} da$$

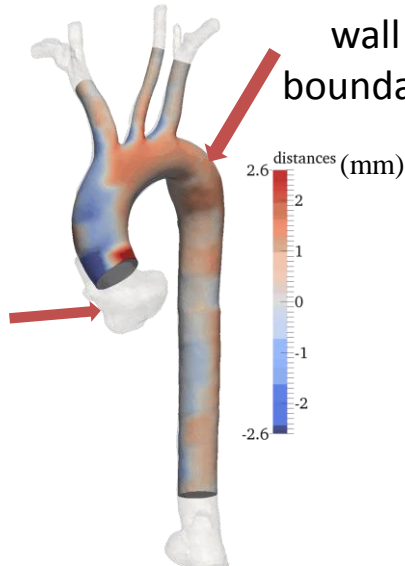
$$P_i = \frac{1}{\text{area}_i} \int_{a_i} p(x, t_n) da$$

Simulated wall boundary

Distance to a sequence of wall motion surfaces (interpolated linearly in time)

$$Z - H(X_n) = D(X_n) = \alpha_k \text{dist}(x + u, S_k) + (1 - \alpha_k) \text{dist}(x + u, S_{k+1})$$

Segmented data



Data-driven Estimation

Goal:

Minimize discrepancy between model observations and real measurements

$$\min_X J(X)$$

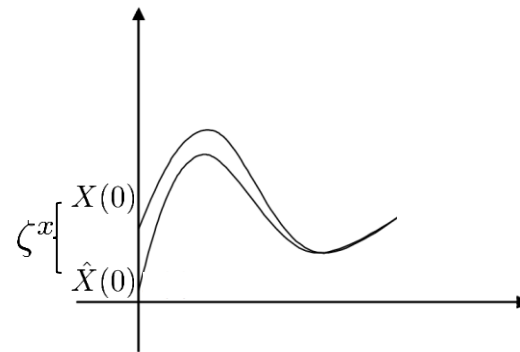
$$J(X) = \int_0^T (Z - H(X))^T (W)^{-1} (Z - H(X)) dt + (X(0) - X_0)^T (P)^{-1} (X(0) - X_0)$$

- “Variational” approach
 - Gradient-based minimization
 - Adjoint method
- “Sequential” approach

$$\dot{\hat{X}} = A(\hat{X}) + K \underbrace{(Z - H(\hat{X}))}_{\text{innovation}}$$

estimate

gain



Sequential Approaches

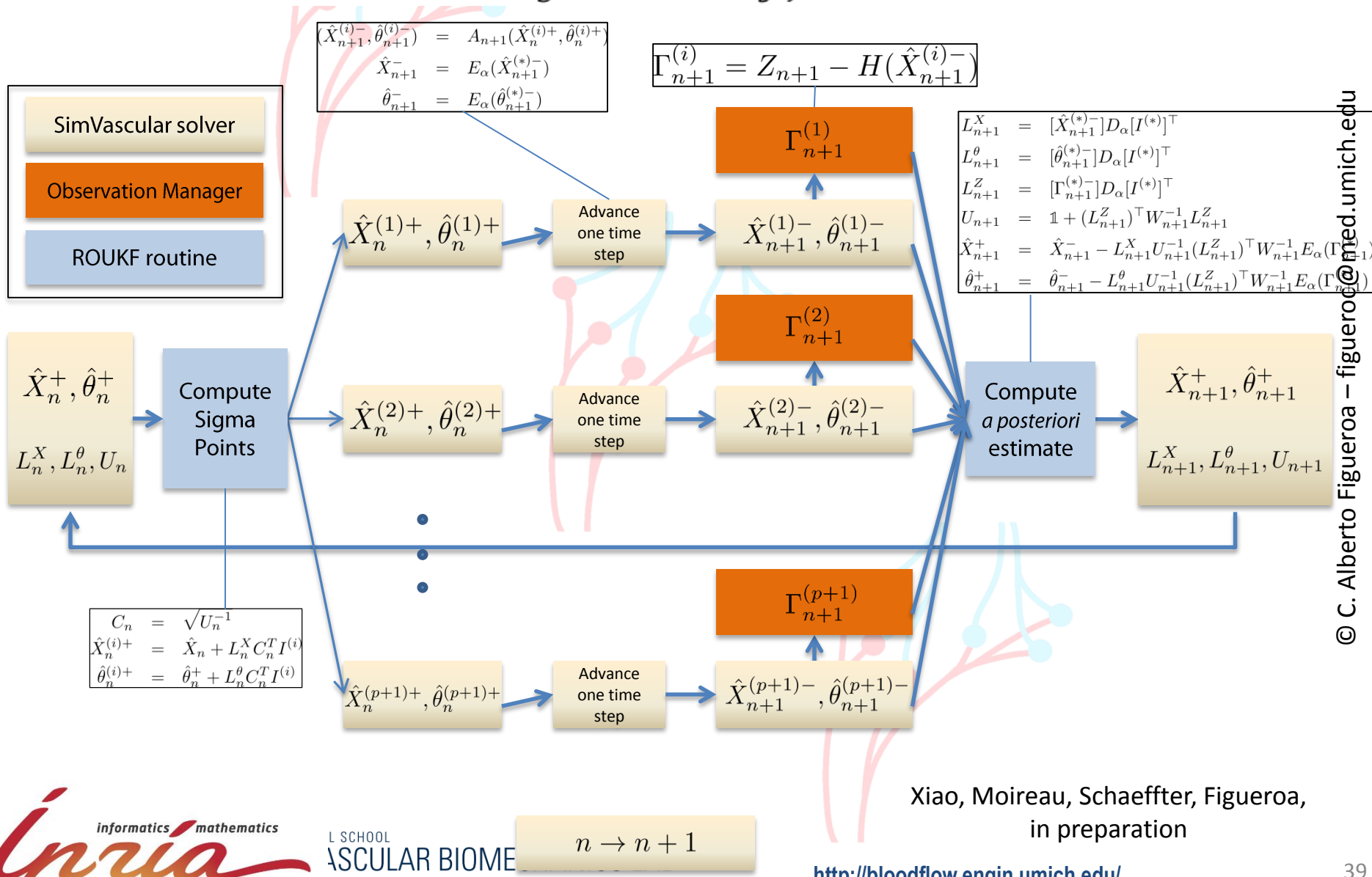
- Classical Kalman filter gives optimal estimates for linear models
- “Unscented” Kalman filter¹ is an effective extension to nonlinear models
- Reduced-order unscented Kalman filter² (ROUKF) enables estimation of an uncertain subset of augmented model states (i.e. the model parameters)
- A set of $(p+1)$ “sigma points” (also called particles) samples the estimation-error probability distribution at each time step (p is the # of parameters)
- In practice, this means running $(p+1)$ concurrent simulations

1. Julier, S. *Proceedings of the 1995 American Control Conference*, 1995

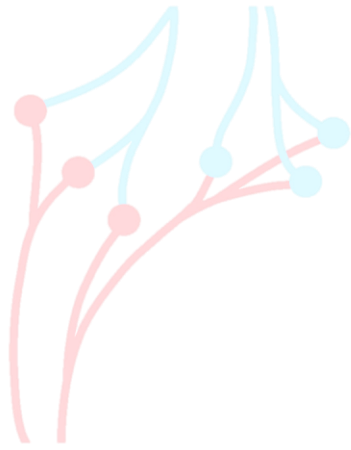
2. Moireau et al., *ESAIM: Control, Optimisation and Calculus of Variations*, 2010

Integration of Open-Source Data Assimilation Library

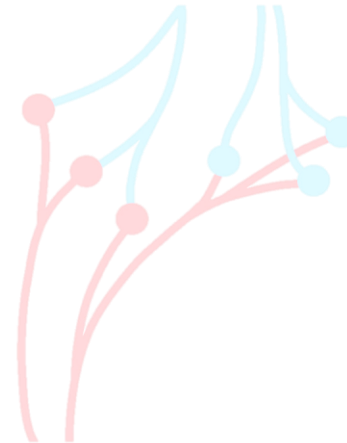
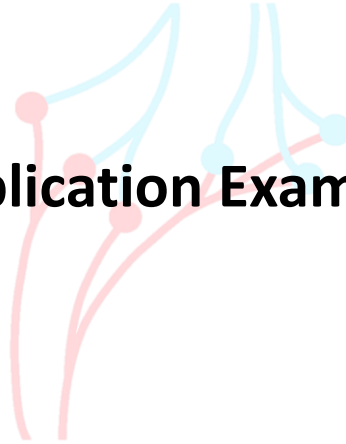
Verdandi generic library for data assimilation



© C. Alberto Figueroa – figueroa@med.umich.edu

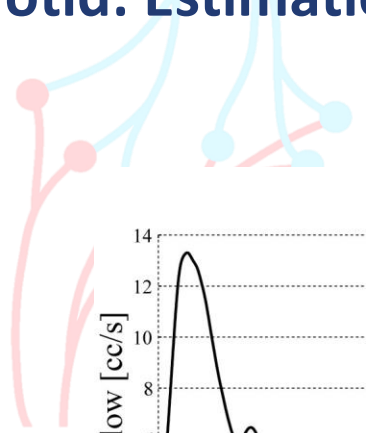


Application Examples

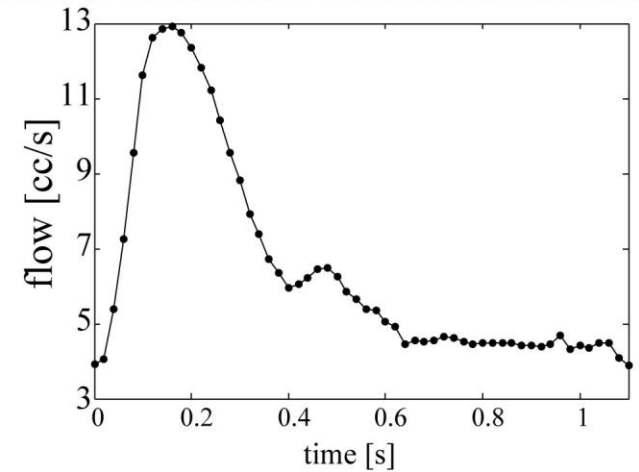
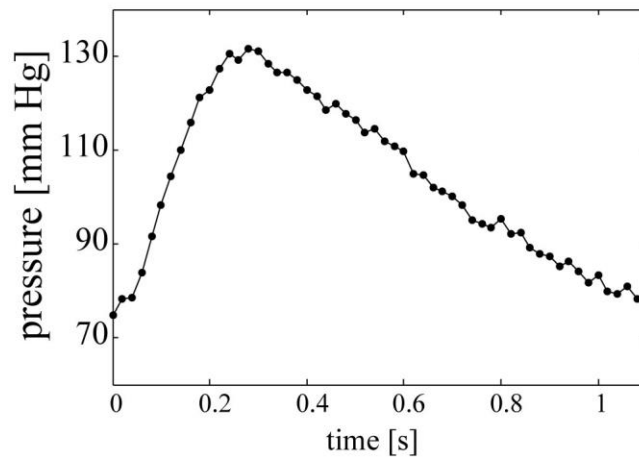
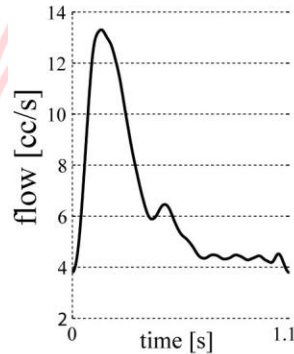
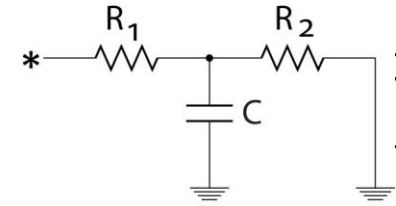
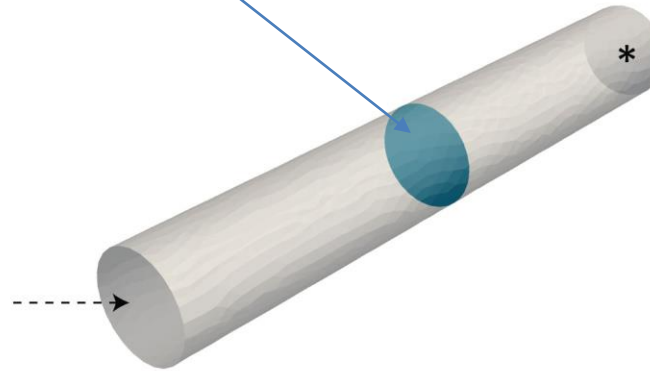


<http://bloodflow.engin.umich.edu/>

Idealized Carotid: Estimation of Windkessel Parameters from P & Q



Observation Plane



Synthetic pressure and flow data
+ Gaussian white noise, 40dB SNR

© C. Alberto Figueroa – figueroa@med.umich.edu

Forward problem:
Parameters values
assumed to be known

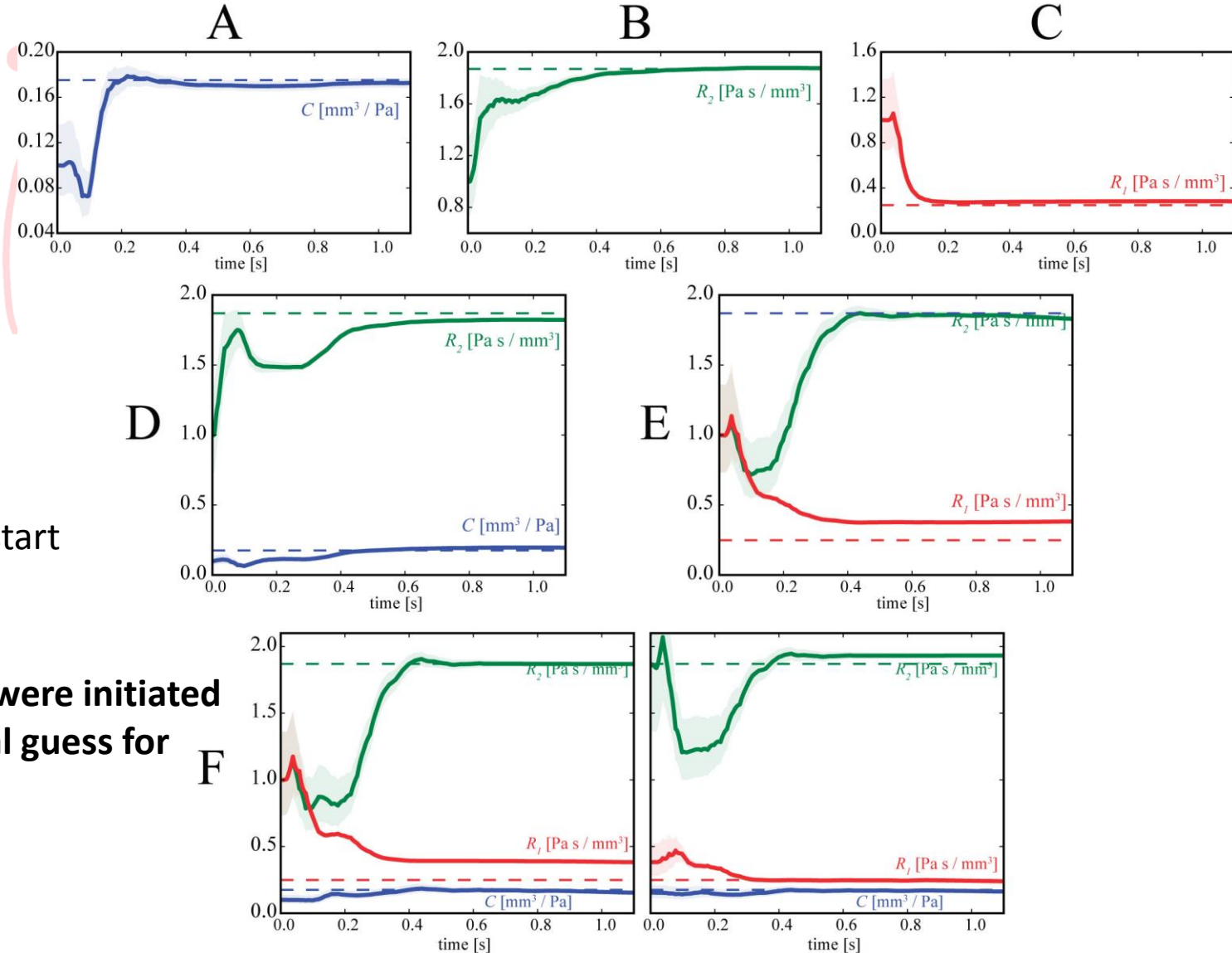
Extract “synthetic data”
from simulation results

Idealized Carotid: Estimation of Windkessel Parameters from P & Q

7 different cases**

- A: C only
- B: R_2 only
- C: R_1 only
- D: R_2 and C
- E: R_1 and C
- F: all, including restart

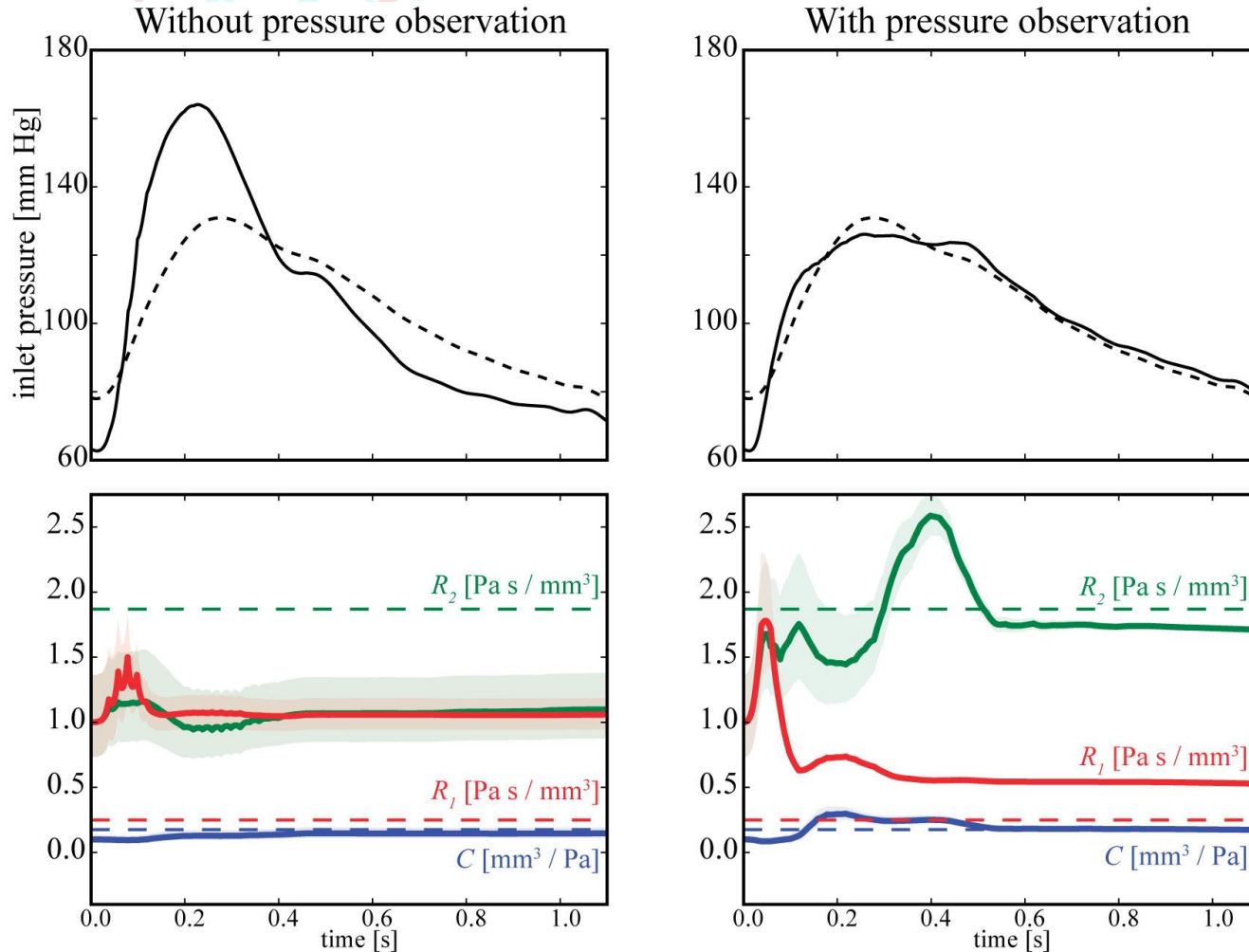
**All these cases were initiated using a good initial guess for the pressure state



Lesson: If we have observations on Q & P, we can estimate any combination of the Windkessel parameters

Idealized Carotid: Estimation of Windkessel Parameters from P & Q

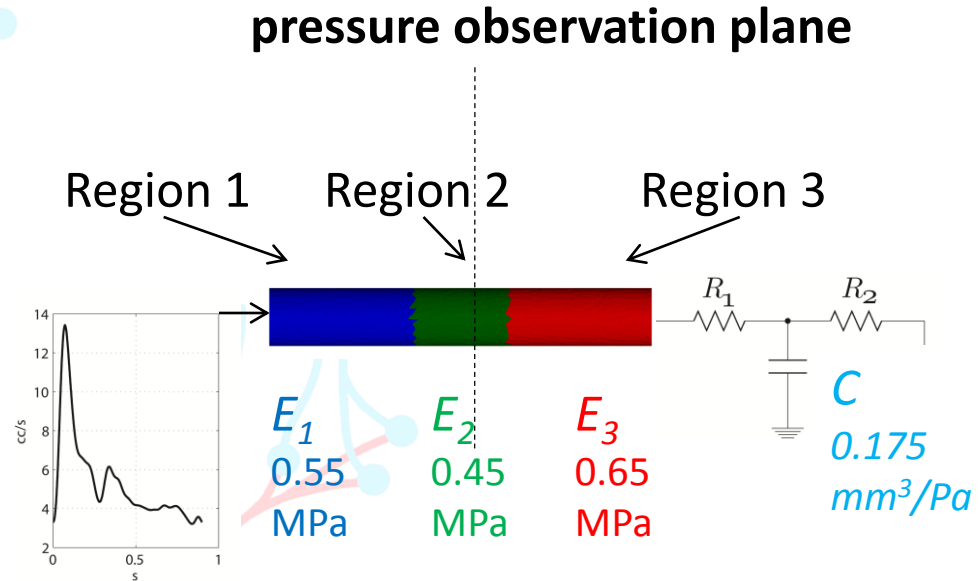
What happens if we don't have a good initial guess for the pressure field?



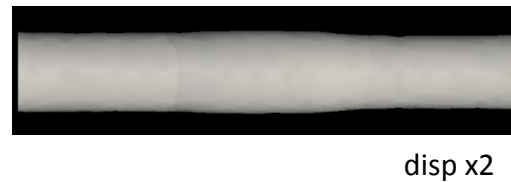
Lesson: If no observation on P, and bad initial guess on state of P, the Windkessel parameters are not identifiable

Idealized Carotid: Estimation of Wall Stiffness + Distal Compliance

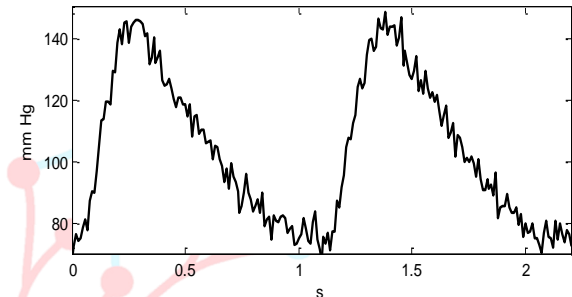
Forward problem:
Parameters values
assumed to be known



Extract “synthetic data”
from simulation results

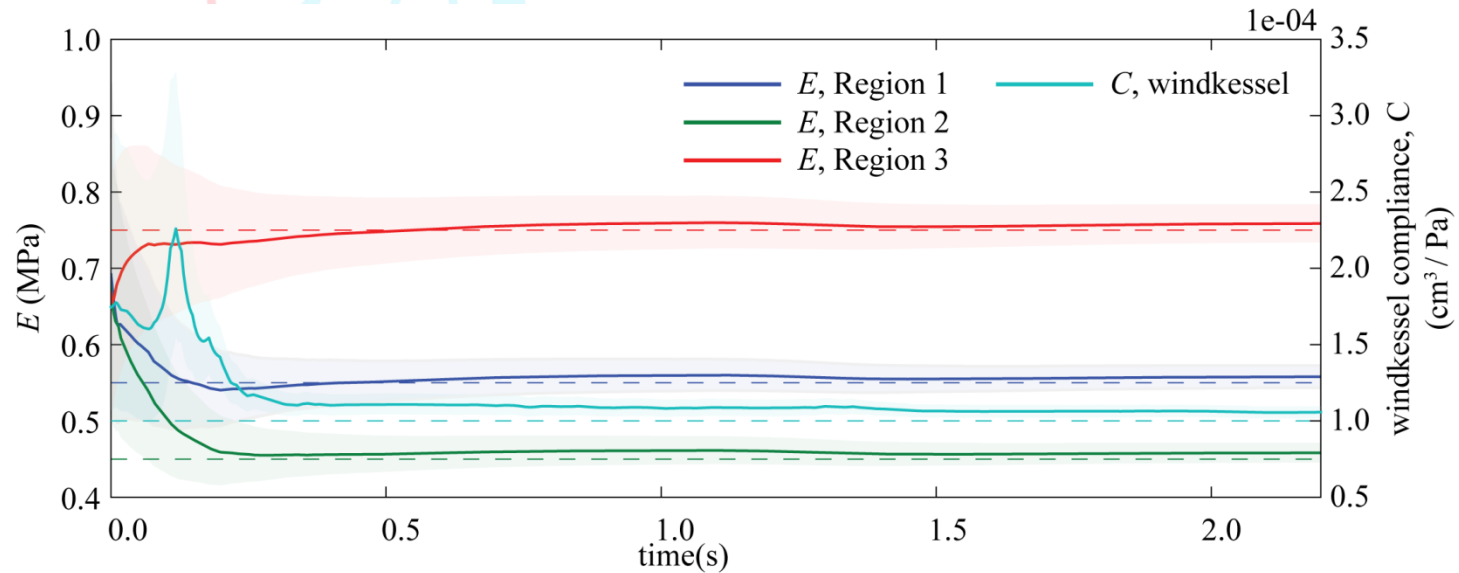


Synthetic
wall motion data



Synthetic pressure data
+Gaussian white noise, 30dB SNR

Idealized Carotid: Estimation of Wall Stiffness + Distal Compliance

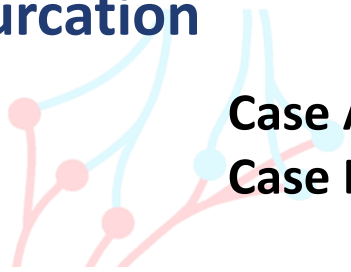


Estimation started with bad initial guesses for parameters but good for state of P

Lesson: If wall motion data and pressure observations are available, we can estimate the total compliance of the system, e.g.:

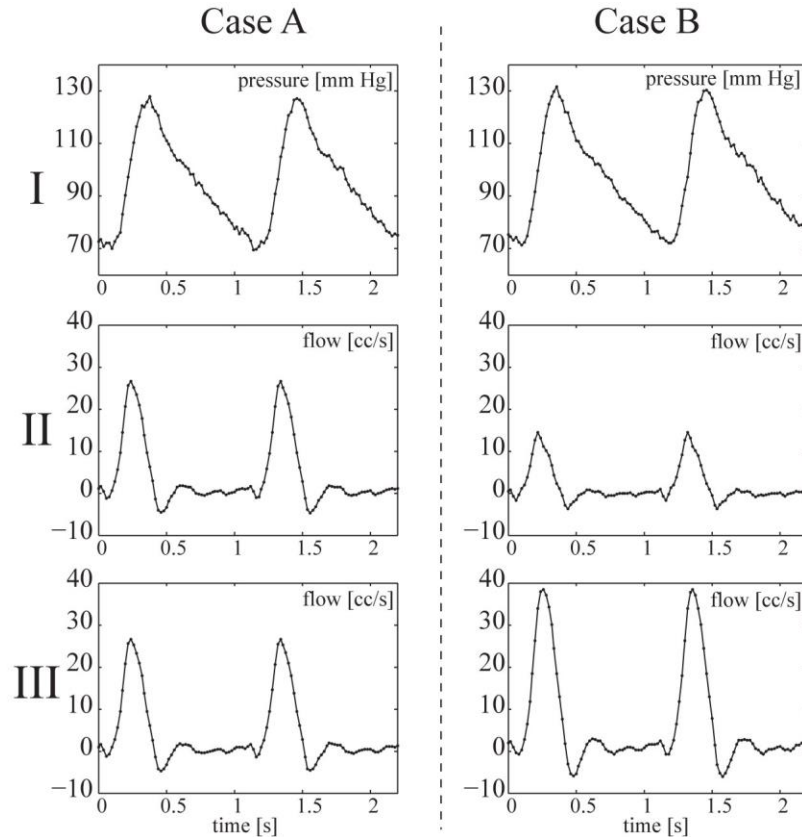
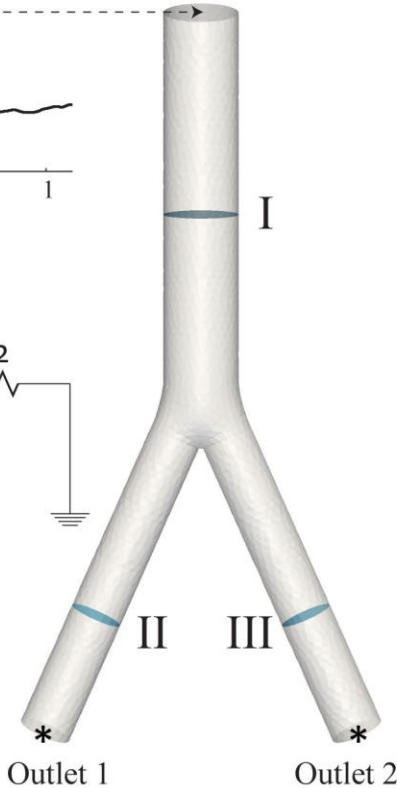
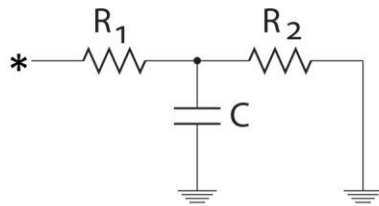
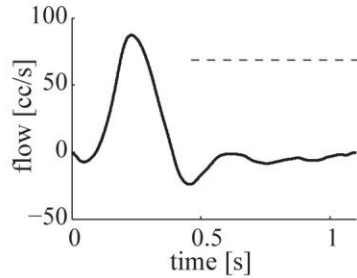
- The proximal compliance (vessel stiffness)
- The distal compliance (Windkessel)

Idealized Bifurcation



Case A: symmetric distal beds

Case B: non-symmetric distal beds



Forward problem:

Parameters values

assumed to be known

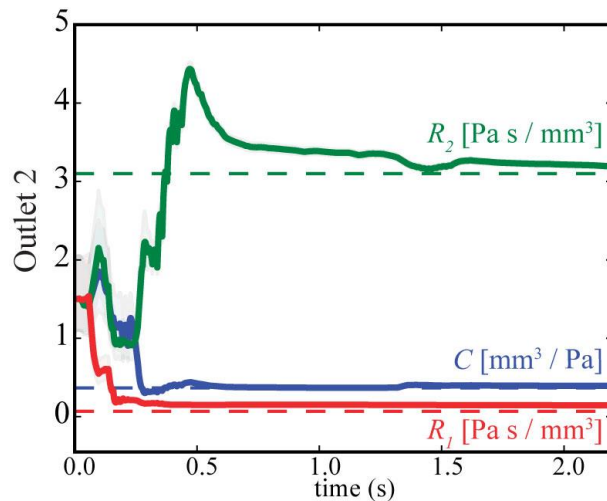
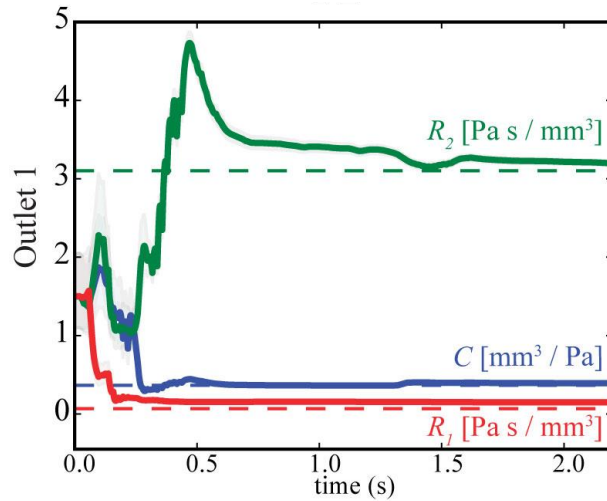
“synthetic data”

Pressure at I

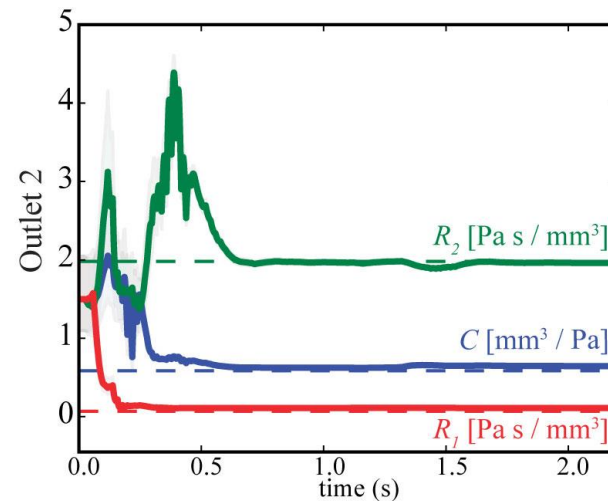
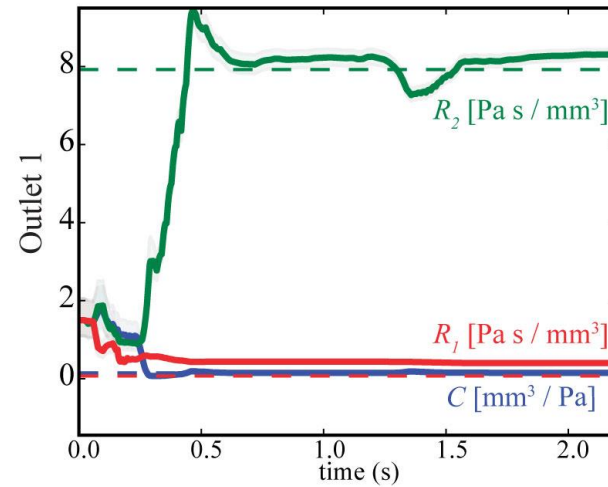
Flows at II and II

Idealized Bifurcation (good initial guess for the state of P)

A: symmetric distal beds



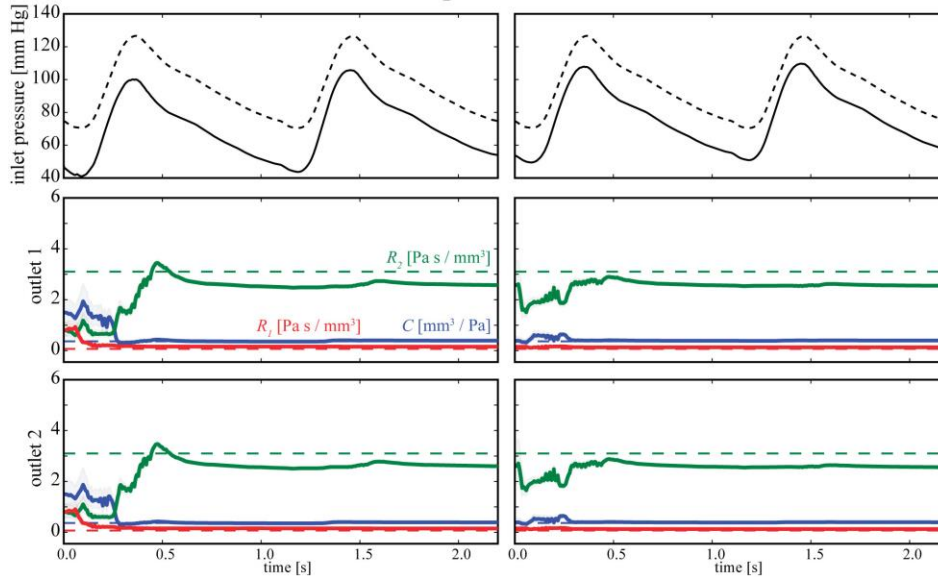
B: non-symmetric distal beds



Lesson: If we have observations on Q & P, we can estimate any combination of the Windkessel parameters for multiple outlets

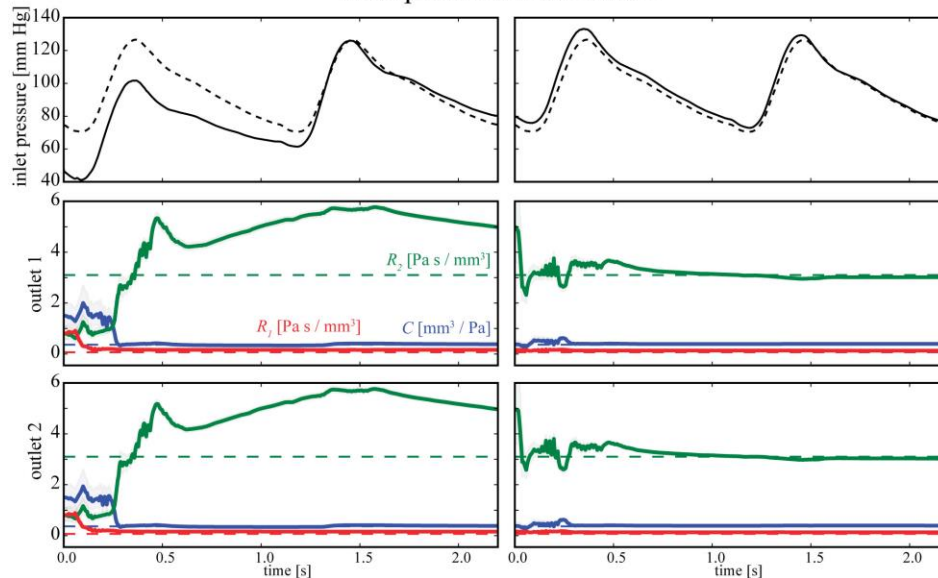
Idealized Bifurcation (bad initial guess for the state of P)

Without pressure observation



Lesson: If no observation on P, and bad initial guess on state of P, the Windkessel parameters are not identifiable

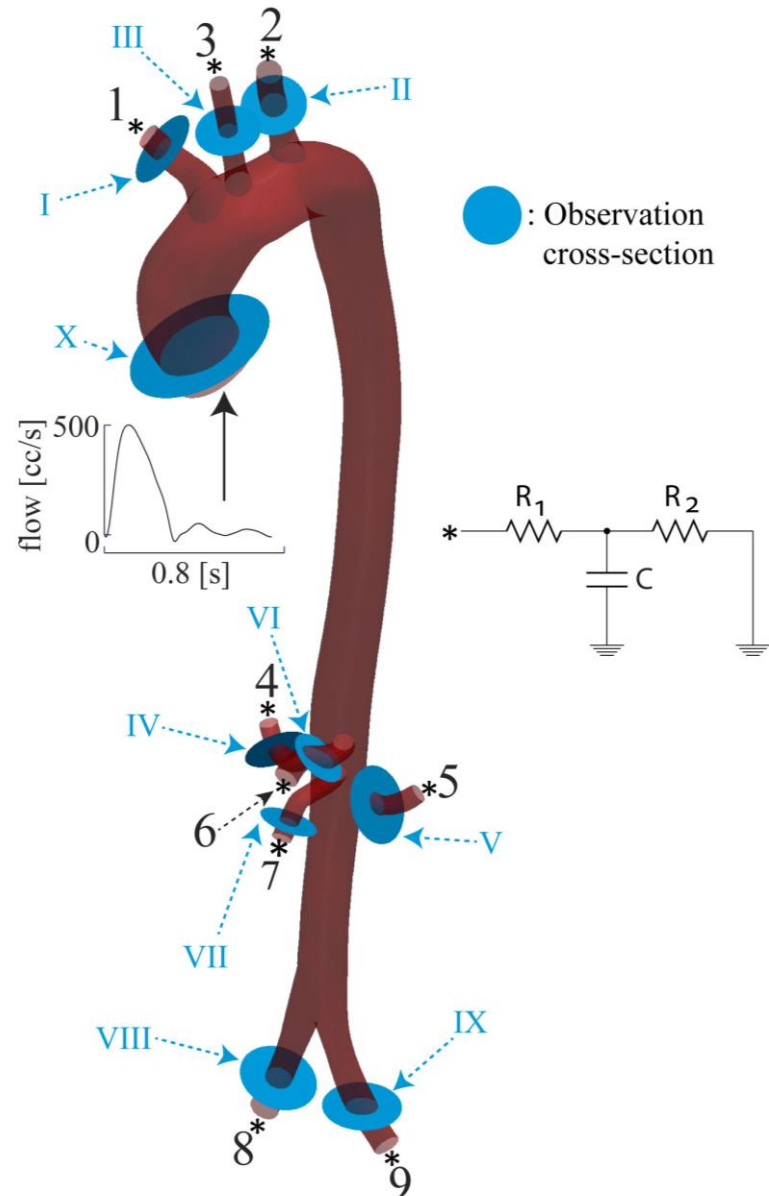
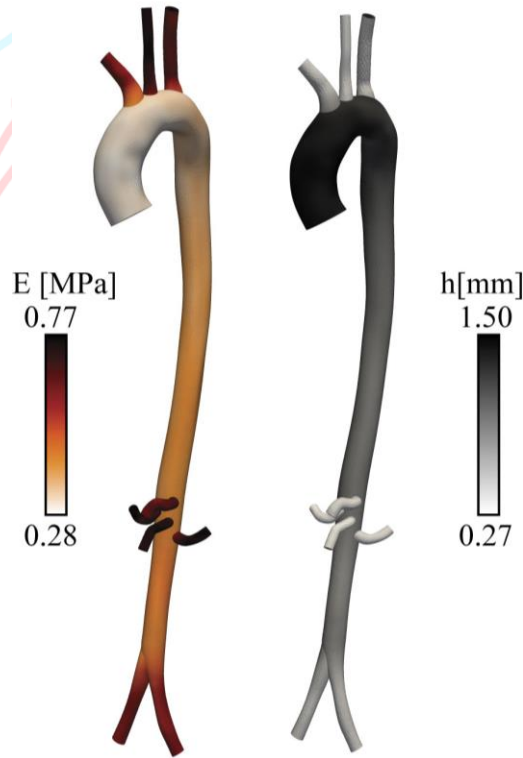
With pressure observation



We need information on Pressure!
(either as initial guess on the state, or a observation)

Full patient-specific aorta (with synthetic data)

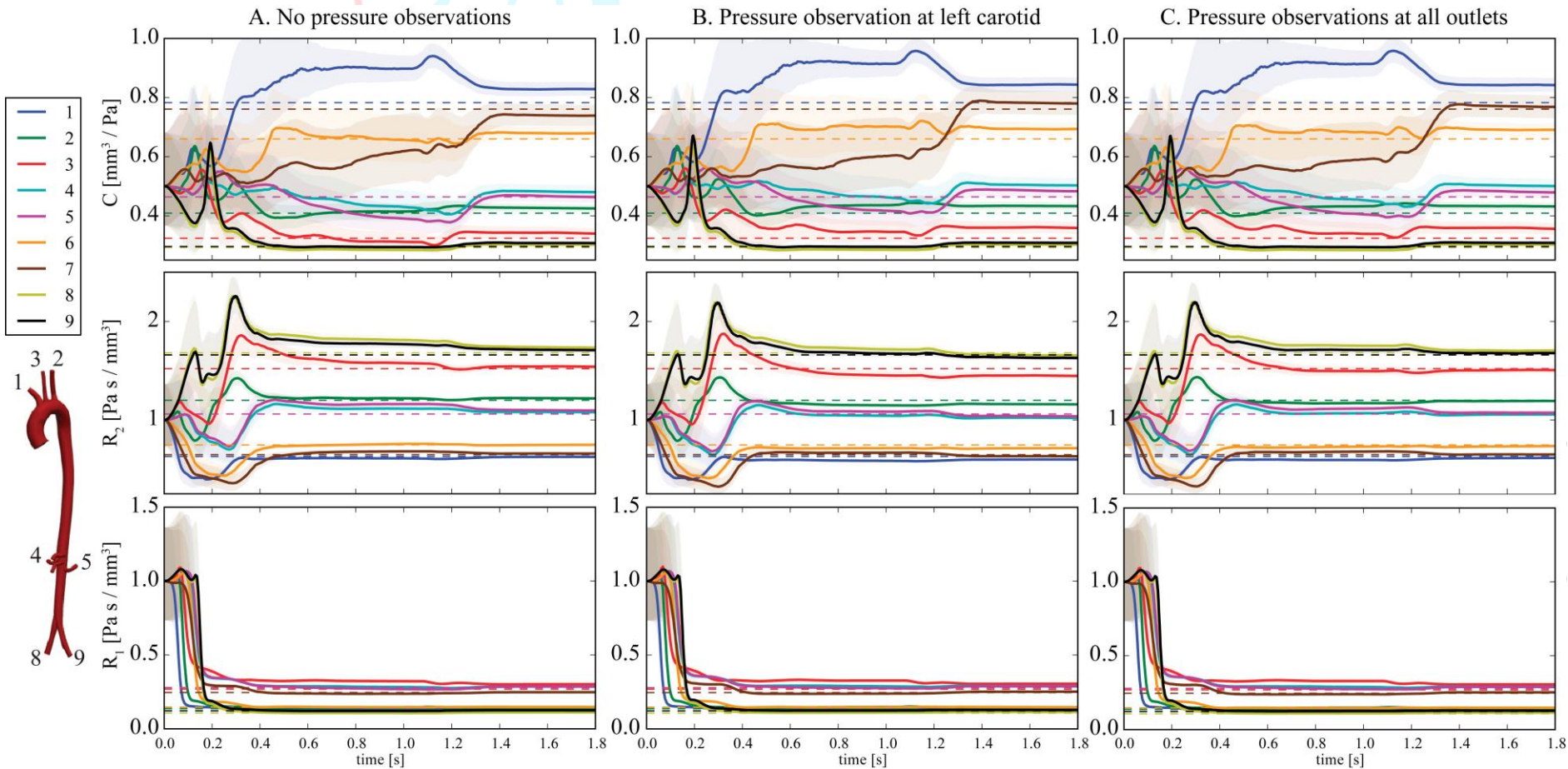
Forward problem:
Parameters values assumed to be known



cross-section	case A (no P obs.)	case B (P obs. left carotid)	case C (P obs. all outlets)
I	Q	Q	P,Q
II	Q	Q	P,Q
III	Q	P,Q	P,Q
IV	Q	Q	P,Q
V	Q	Q	P,Q
VI	Q	Q	P,Q
VII	Q	Q	P,Q
VIII	Q	Q	P,Q
IX	Q	Q	P,Q

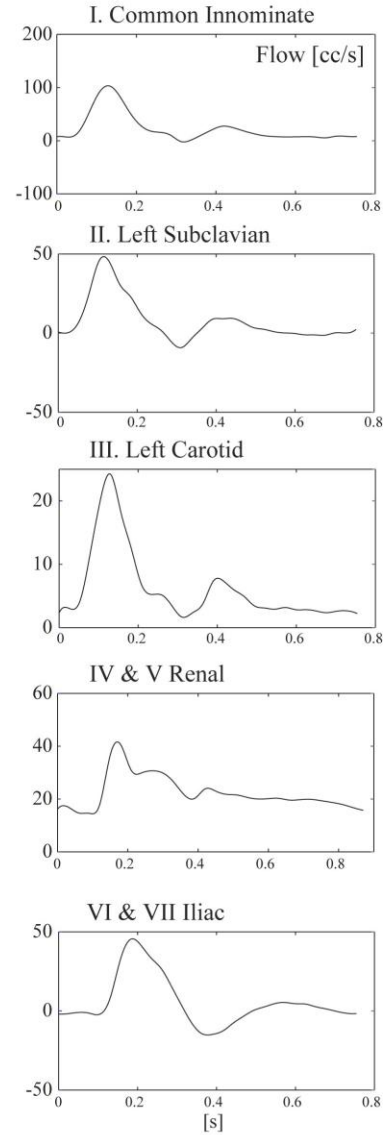
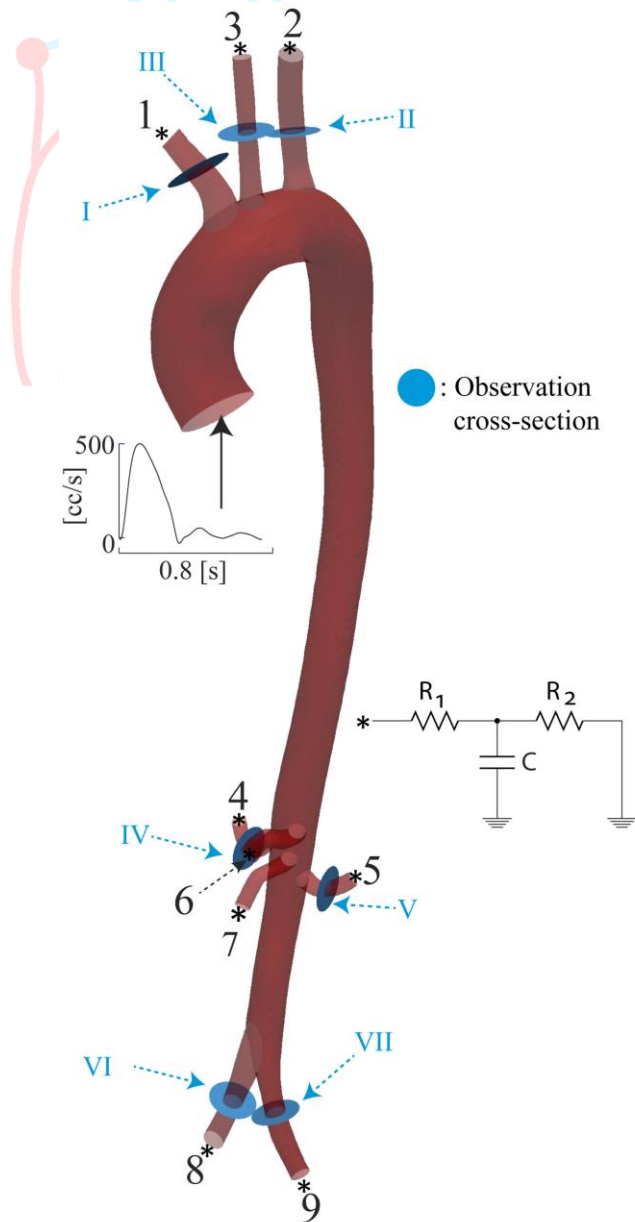
© C. Alberto Figueroa – figueroc@med.umich.edu

Full patient-specific aorta (with synthetic data)

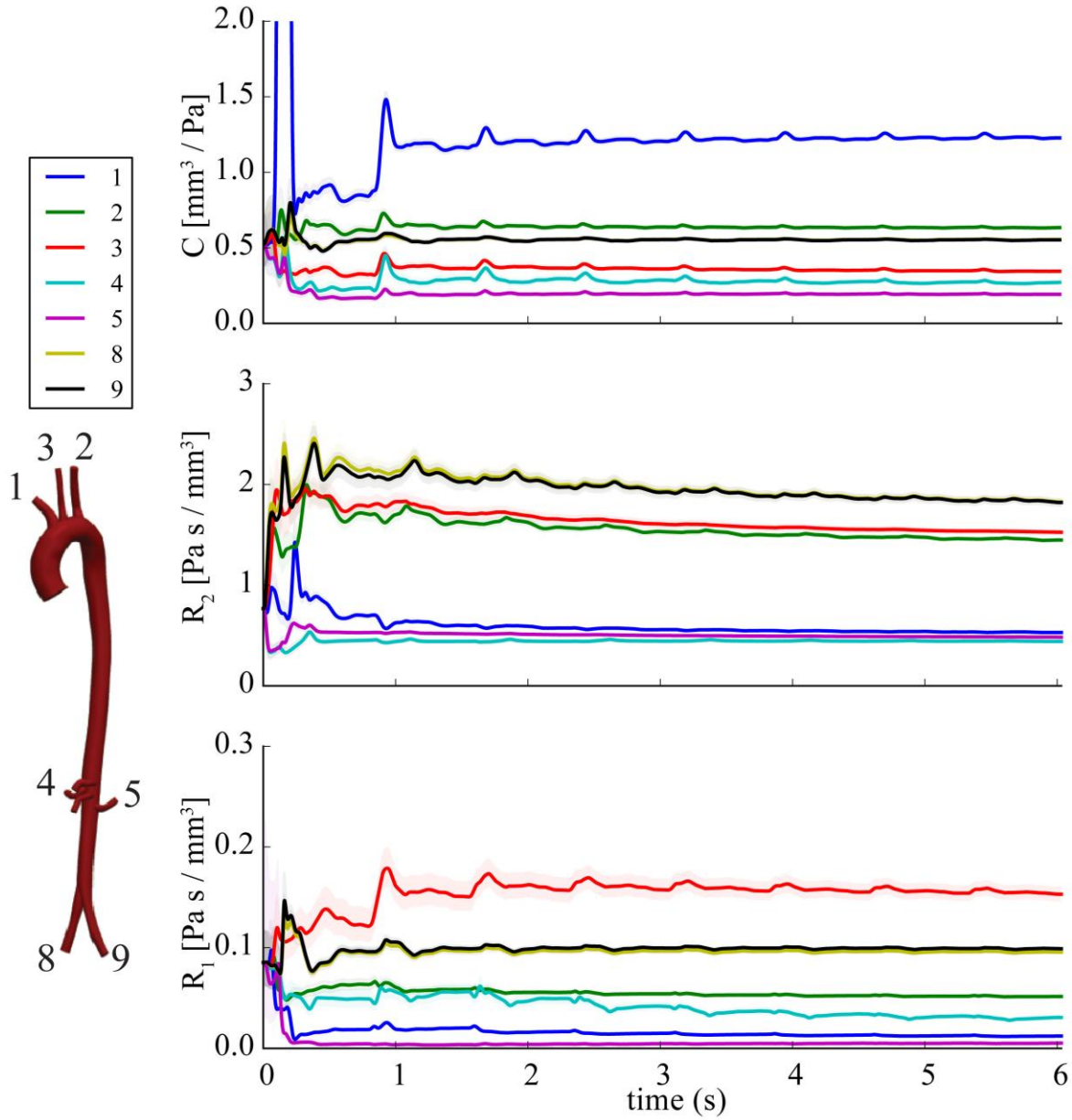


Lesson: surprisingly, even without an observation on pressure, things work if a good initial estimate on the pressure state is known (which of course means we know something about the pressure)

Full patient-specific aorta (with real data)



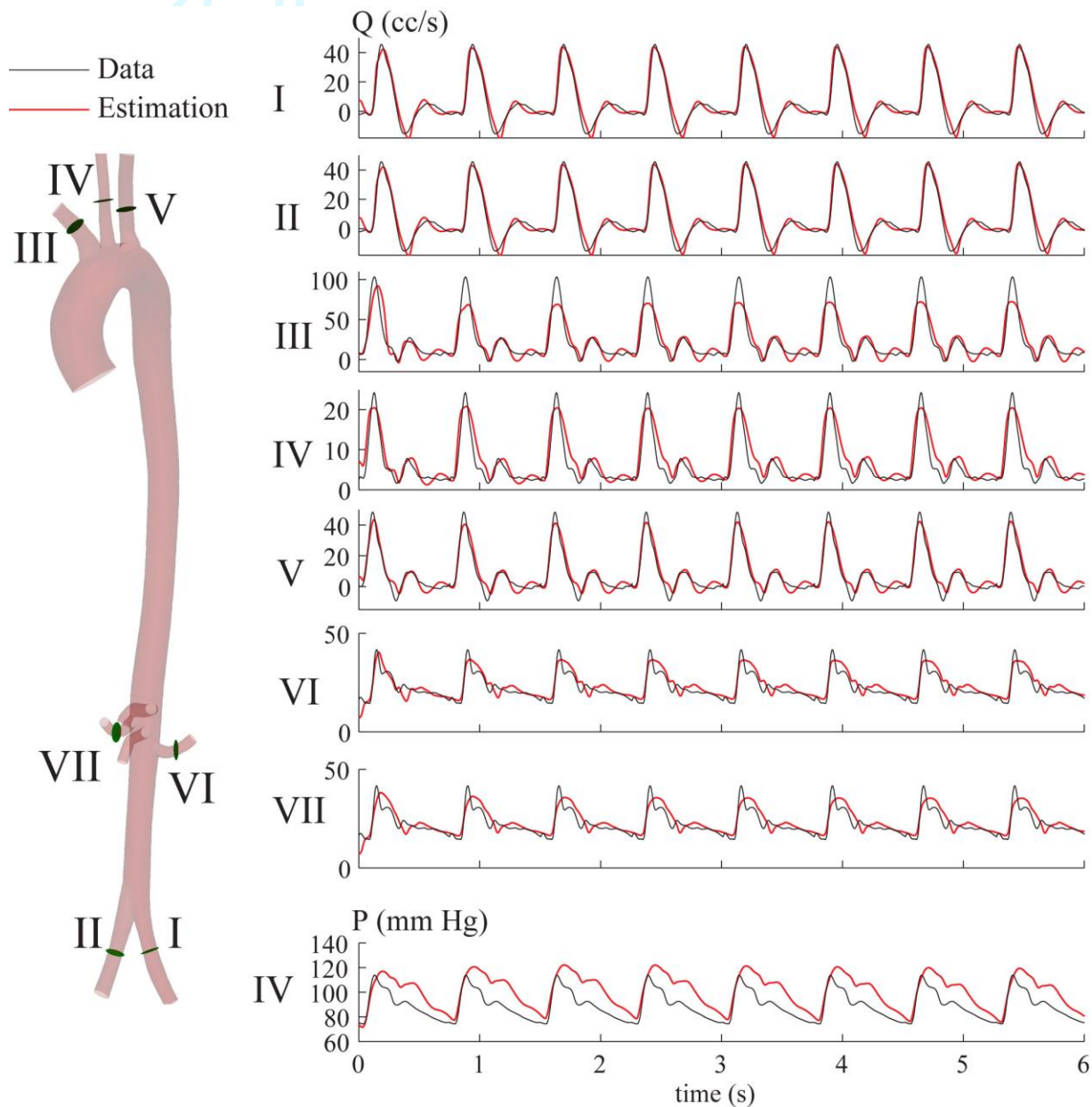
Full patient-specific aorta (with real data)



Lesson: all parameters are identifiable: estimates on C , R_1 and R_2 remain constant after several cycles



Full patient-specific aorta (with real data)



Conclusions

- Computational for CV modeling usually rely on a large number of parameters
- Estimating these parameters is often the most time consuming and non-systematic task of the modeling process
- 1D techniques, combined with physics-based knowledge of the circulation can be used to quickly estimate the first round of material parameters for the 3D techniques
- Automatic techniques for efficient and automatic material & BC parameter estimation are important to drive both translational and fundamental hemodynamic simulation