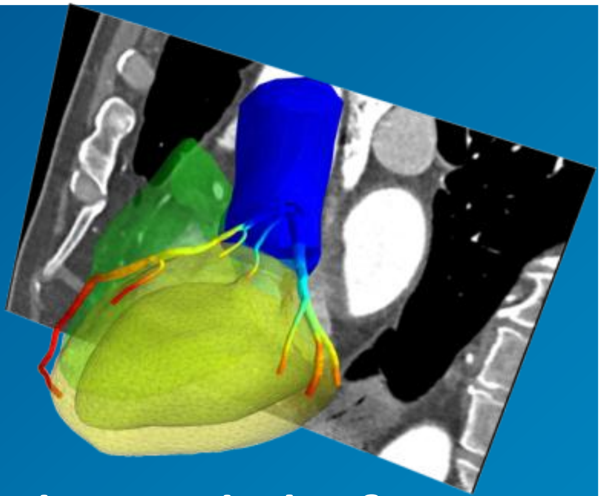

Learning Patient-Specific Lumped Models for Interactive Coronary Blood Flow Simulations

Paper #168, Poster F-5

Hannes Nickisch, Yechiel Lamash, Sven Prevrhal,
Moti Freiman, Mani Vembar, Liran Goshen and Holger Schmitt
October 08, 2015

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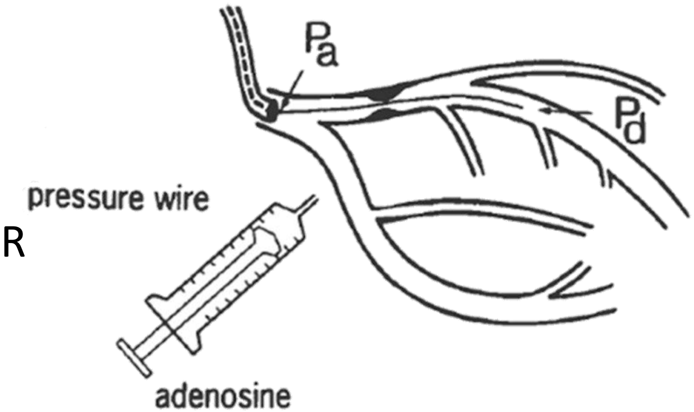
Overview: FFR and FFR-CT



- Significance of a coronary stenosis assessed by FFR
- FFR = Fractional Flow Reserve = Pd/Pa

- FFR: measured through invasive cathlab procedure through a pressure wire
- FFR-CT: simulated from a routine cardiac CTA scan using a biophysical model
- Our contribution: Interactive simulation using lumped models

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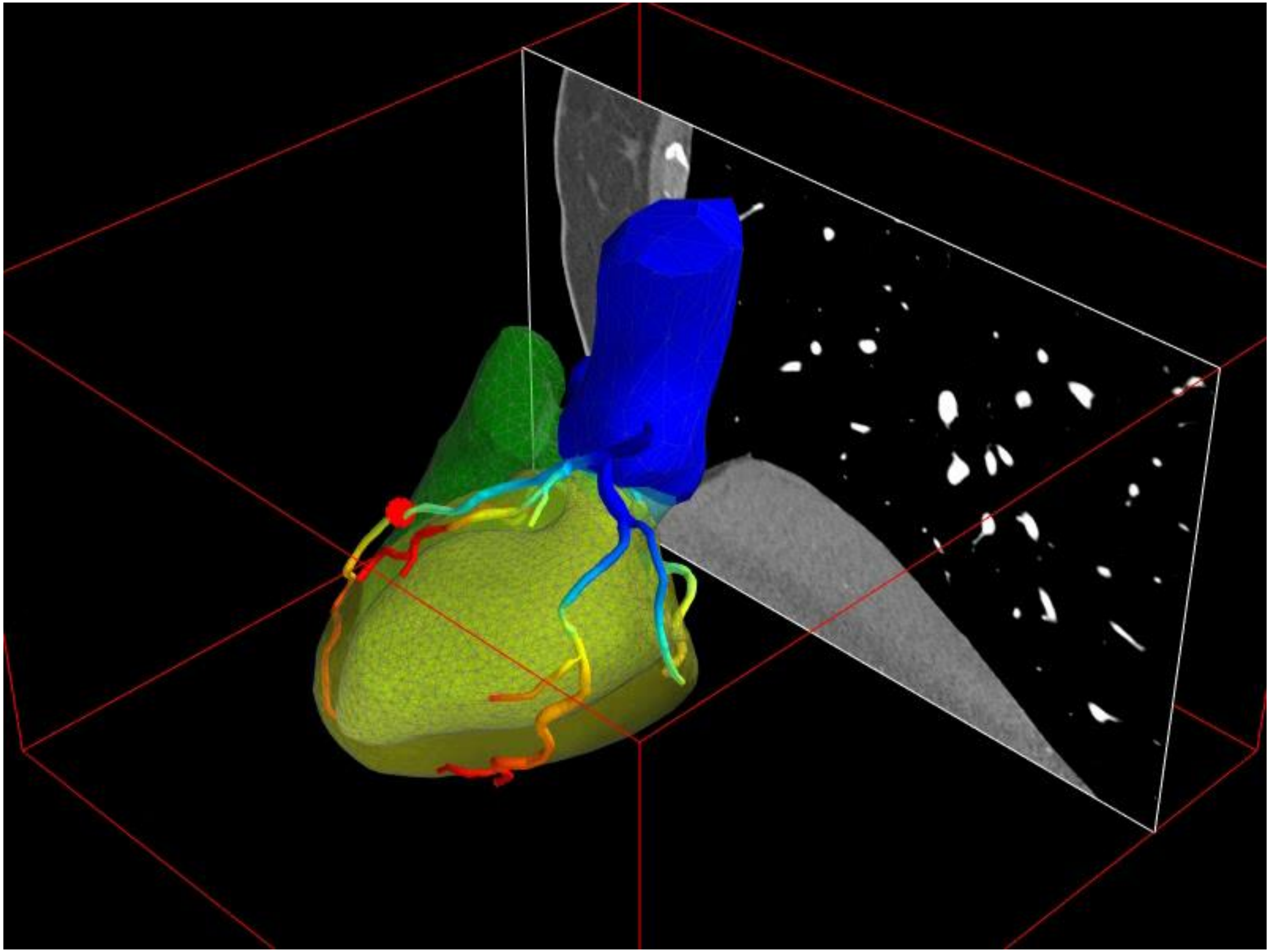
Visualisation



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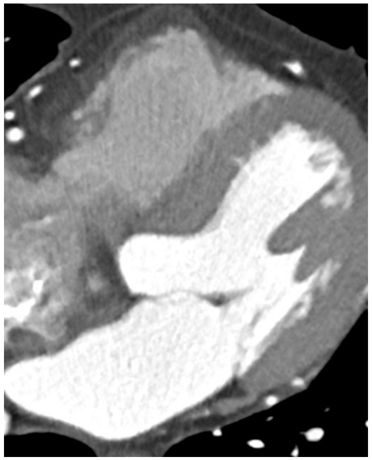
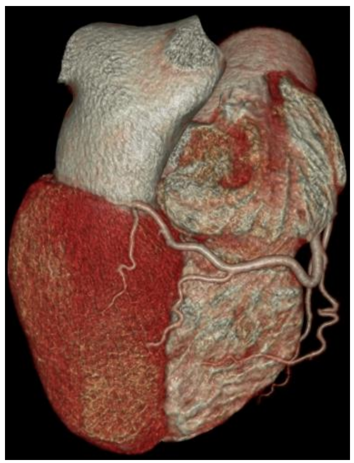
Workflow

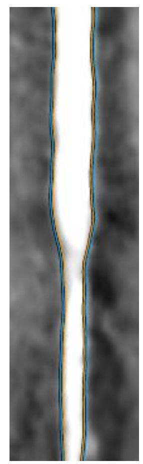
(a) Standard coronary CTA scan



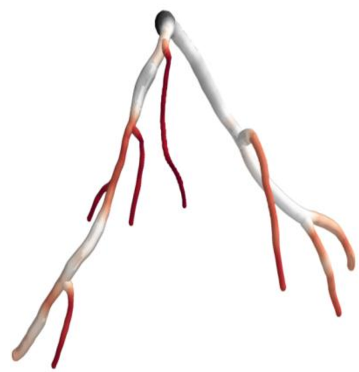
(b) Automatic cardiac segmentation



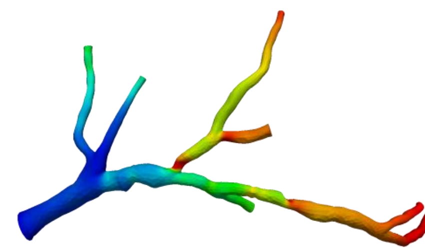
(c) Coronary lumen segmentation



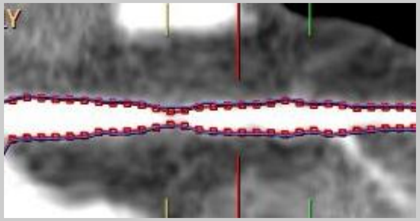
(d) Coronary tree (centerline+cross sections)



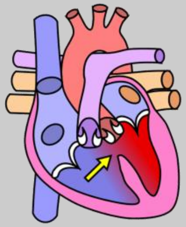
(e) FFR simulation



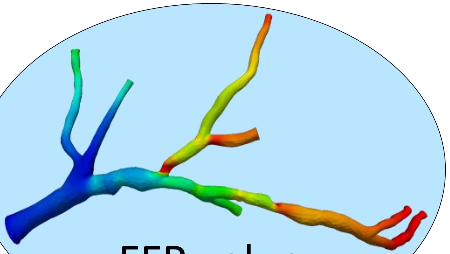
Simulation: Input and Output



Vessel Segmentation

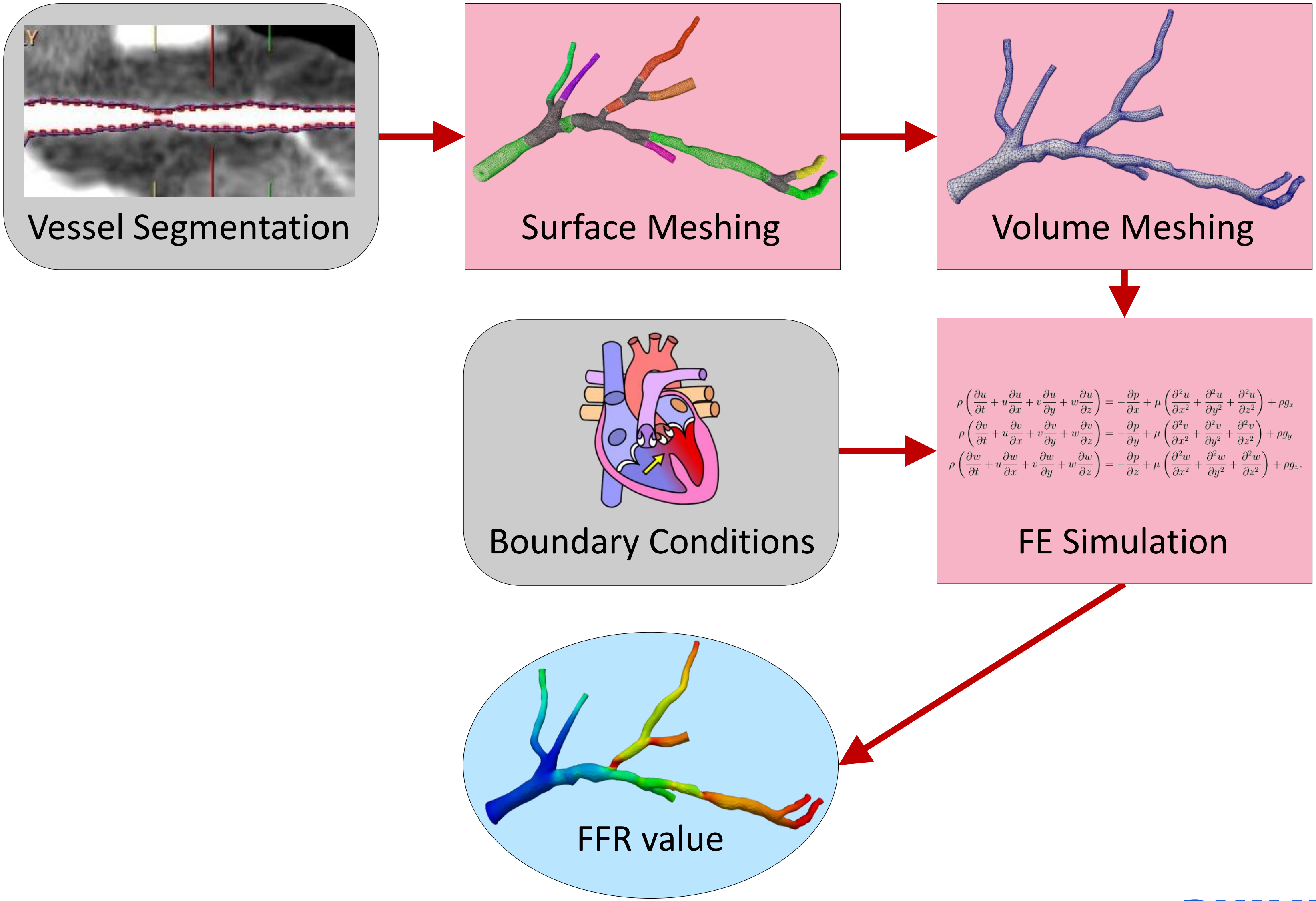


Boundary Conditions

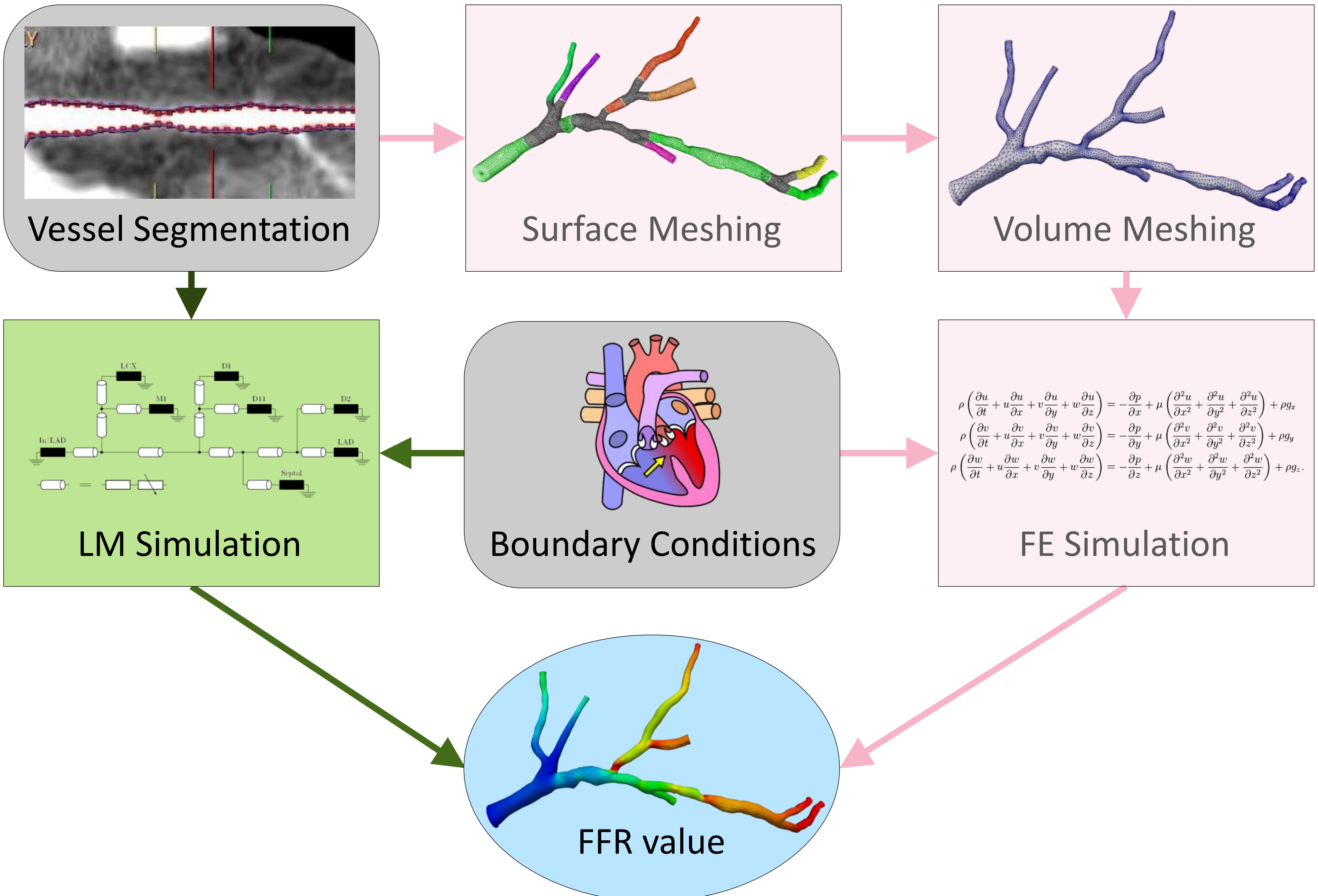


FFR value

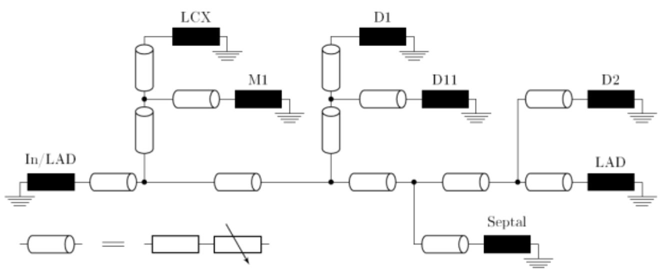
Simulation Pipeline: Finite Elements (FE)



Simulation Pipeline: Lumped Model (LM)

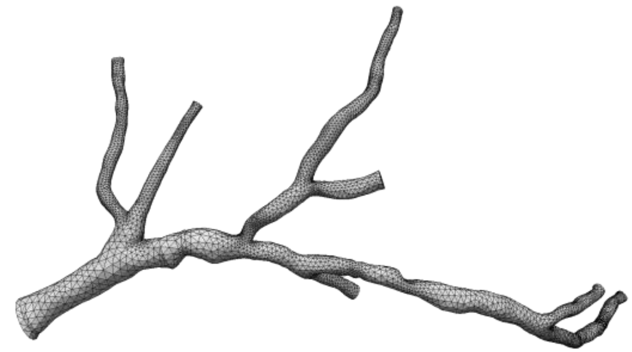


Lumped Models



$$\begin{bmatrix} \mathbf{A}_R \mathbf{R}^{-1} \mathbf{A}_R^\top & \mathbf{A}_P \\ \mathbf{A}_P^\top & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{q} \\ \mathbf{f}_P \end{bmatrix} = \begin{bmatrix} -\mathbf{A}_F \hat{\mathbf{f}}_F \\ \hat{\mathbf{p}}_P \end{bmatrix} + \begin{bmatrix} -\mathbf{A}_V \varphi^{-1}(\mathbf{A}_V^\top \mathbf{q}) \\ \mathbf{0} \end{bmatrix}$$

$$\approx$$

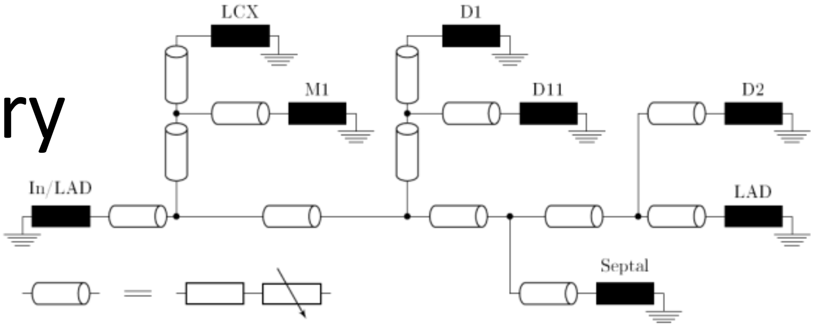


$$\rho(\partial \mathbf{v}/\partial t + \mathbf{v} \cdot \nabla \mathbf{v}) = -\nabla p + \mu \nabla^2 \mathbf{v} + \mathbf{f}$$

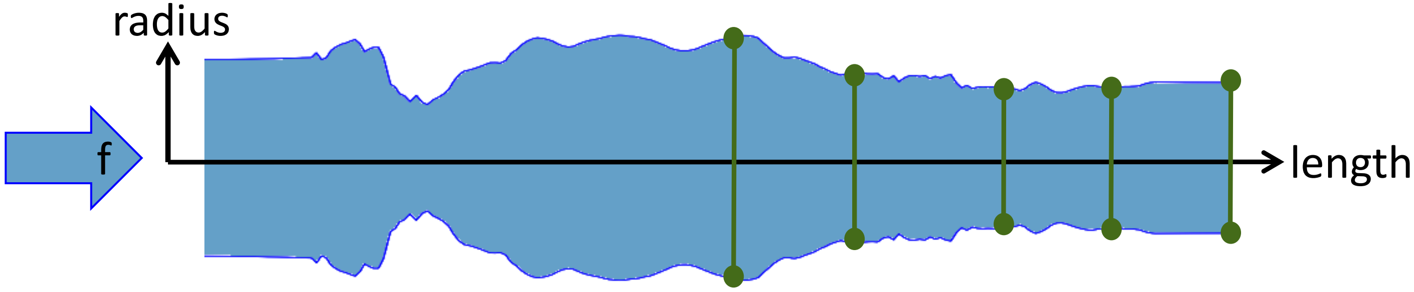
- Fast: extremely quick to evaluate
- Simple: no surface or volume meshing required
- Already there: most FE boundary conditions are lumped

- Similar to electrical circuits via hydraulic analogy
  - voltage ≡ pressure, current ≡ volumetric flow rate
  - wire ≡ pipe, resistance ≡ constricted pipe,
- Non-linear 0d models aka reduced order approximation to 3d FE models
- Fit using statistical machine learning and hydraulic features

Lumped Model from Geometry



- Segment transfer function = sum of local (cross sectional) transfer functions



f: volumetric flow rate

p: pressure

$$\Delta p(f) = \Delta p_1(f) + .. + \Delta p_{n-1}(f) + \Delta p_n(f)$$

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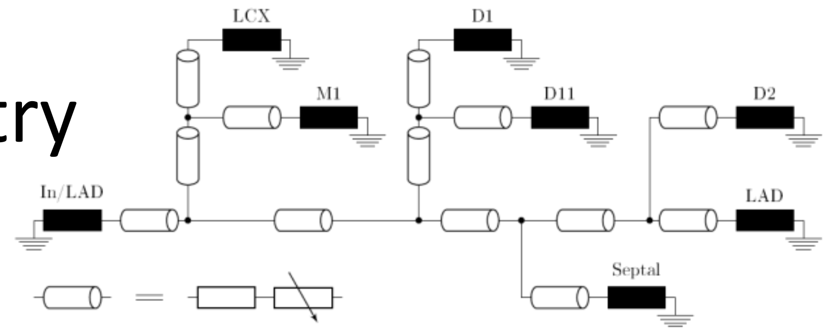
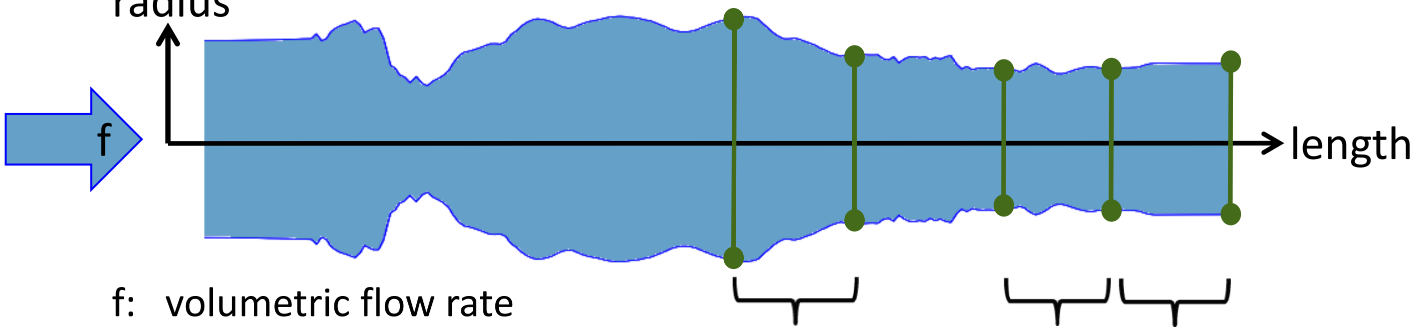
Lumped Model from Geometry



- Segment transfer function = sum of local (cross sectional) transfer functions

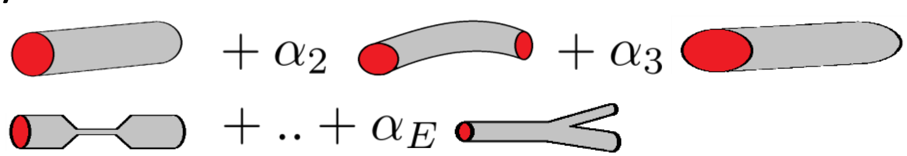


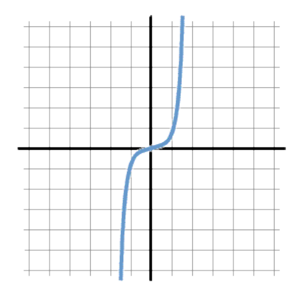
f: volumetric flow rate

p: pressure

$$\Delta p(f) = \Delta p_1(f) + .. + \Delta p_{n-1}(f) + \Delta p_n(f)$$

- Local transfer function = weighted sum of effect transfer functions
  - Symmetric polynomial from literature
  - $\Delta p_i(f) = \alpha_1 \;\; + \alpha_2 \;\; + \alpha_3 \;\; + \alpha_4 \;\; + .. + \alpha_E$





  - Poiseuille, Bernoulli, ovality, expansion, constriction, bifurcation, curvature, ..

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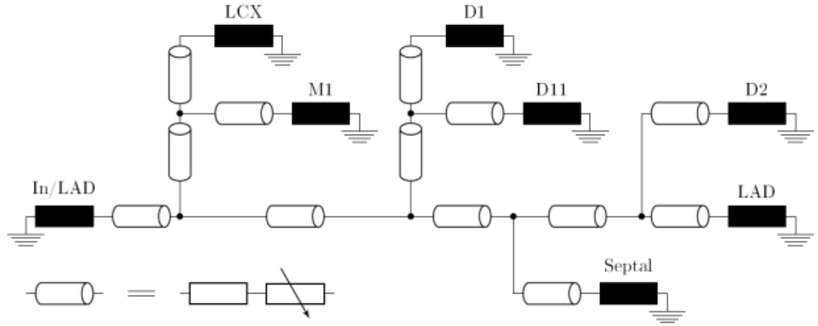
Lumped Model Learning



- Adjust effect weights $\boldsymbol{\alpha}$ so that lumped model $\hat{\mathbf{p}}_i$ matches CFD simulation $\mathbf{p}_i$
- Simulate a training data base of cases $(\mathbf{f}_i^{CFD}, \mathbf{p}_i^{CFD})$ using OpenFOAM

- Lumped Model estimate $\hat{\mathbf{p}}_i^{LM} = \mathbf{C} \sum_{e=1}^{E} \alpha_e \Delta \mathbf{p}_e(\mathbf{f}_i^{CFD})$
- Nonnegative least squares fit $\boldsymbol{\alpha}_* = \arg\min_{\boldsymbol{\alpha} \succeq \mathbf{0}} \sum_i \left\| \mathbf{p}_i^{CFD} - \hat{\mathbf{p}}_i^{LM} \right\|^2$

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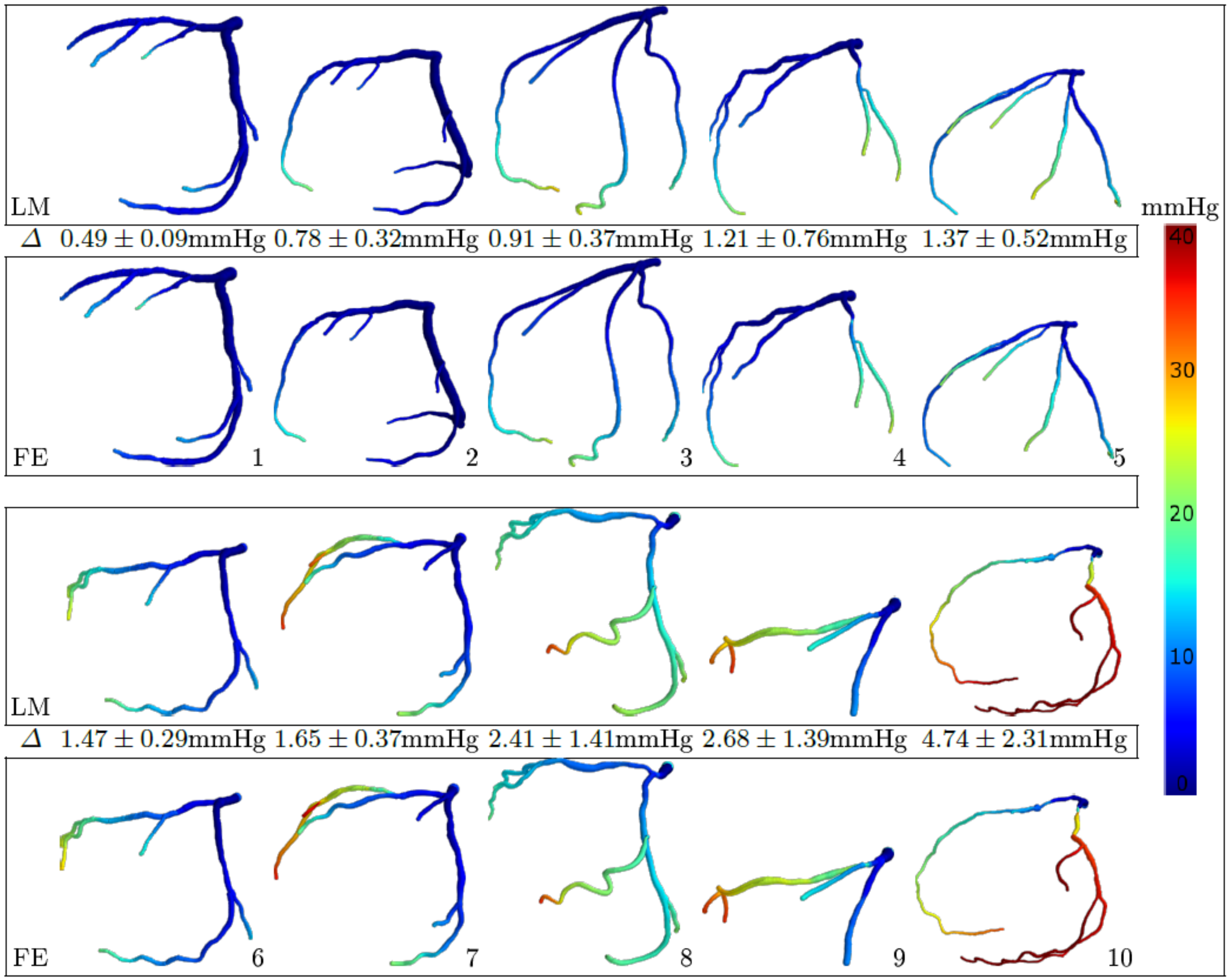
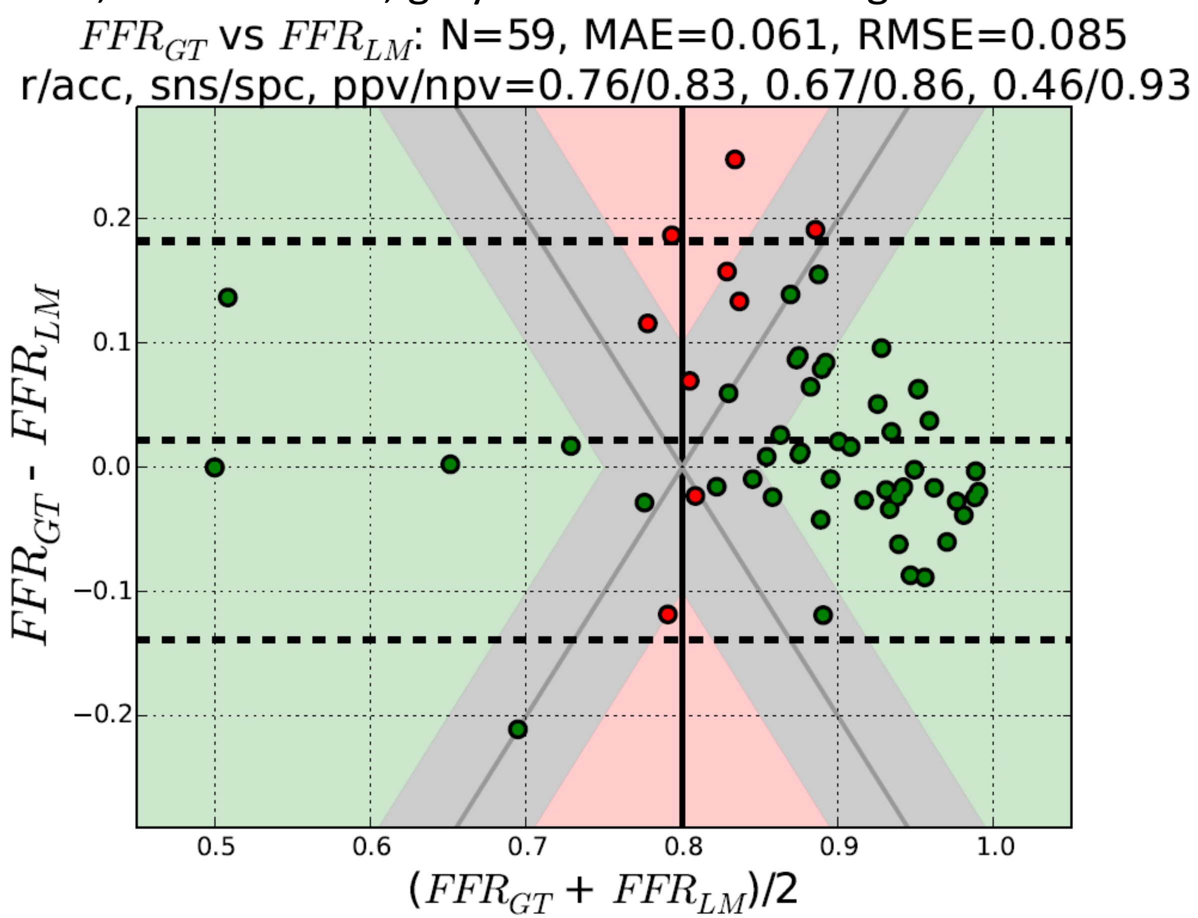
Learning Validation

- E=8 coefficients α, 35 coronary trees, 10 flow levels, 20fold resampling
- MAE 2.76±0.56mmHg, runtime ≤2min



Ground Truth Validation

- 41 patients, 59 invasive FFR measurements (GT)
- Clinical FFR threshold 0.8 → AUC=0.77
- Green: correct, red: incorrect, gray: intrinsic error margin



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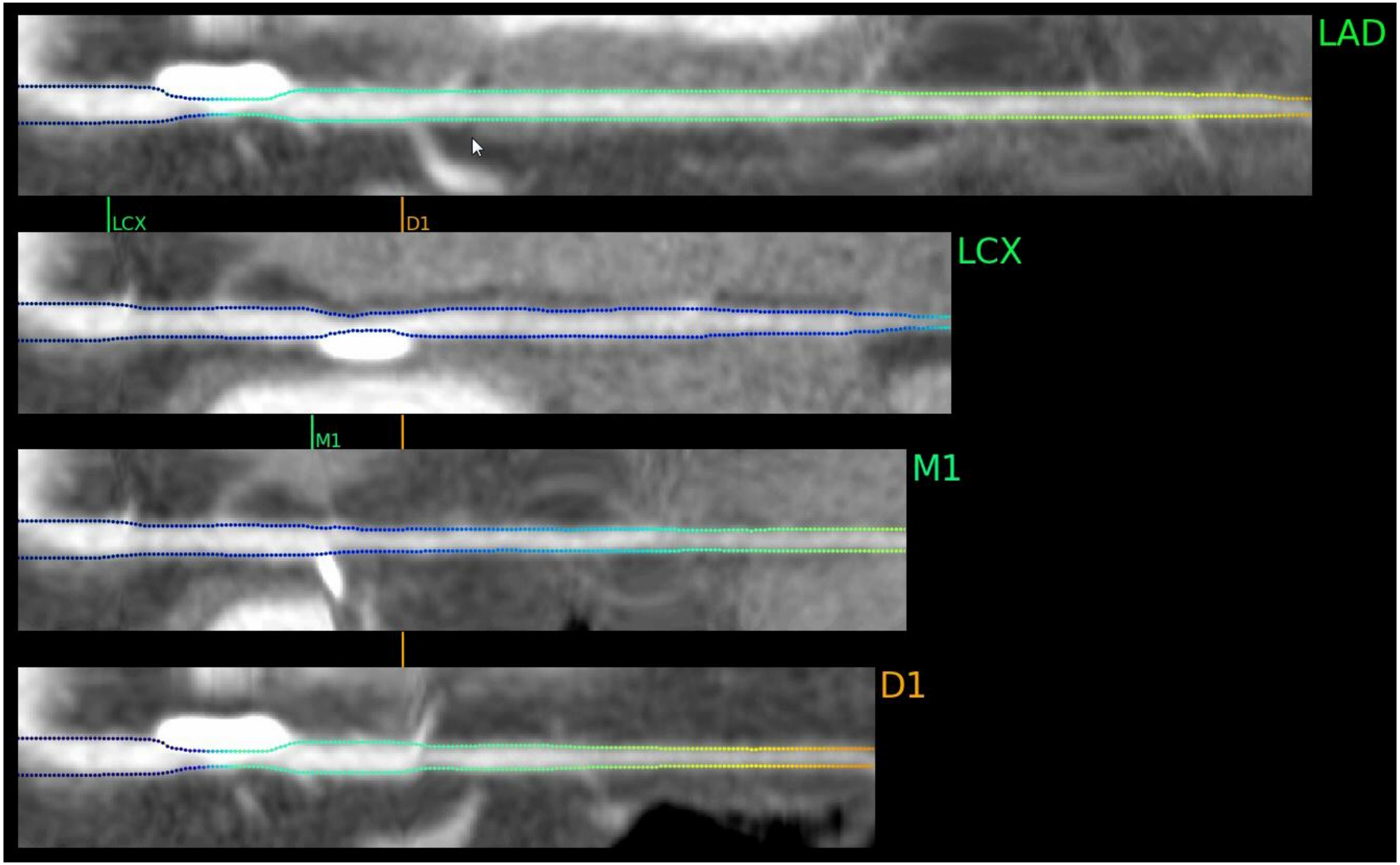
Interactive Prediction



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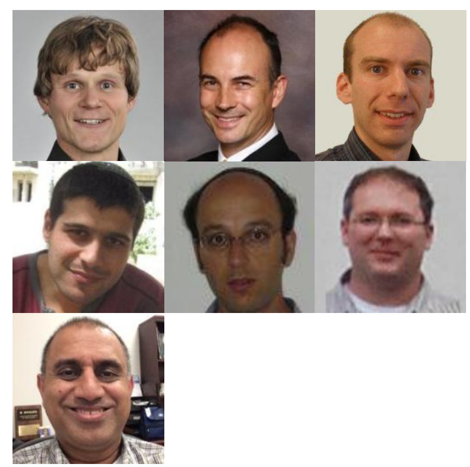
Summary and Discussion

- Simple and fast surrogate model to FE simulations of fluid flow
- Trained using machine learning
- Evaluated on FFR prediction tasks
- Allow for interactive computation of hemodynamic parameters
- Applicable to general networks of elongated structures

- Hamburg (Research)
  Hannes Nickisch, Sven Prevrhal, Holger Schmitt
- Haifa (Advanced Development)
  Yechiel Lamash, Moti Freiman, Liran Goshen
- Cleveland (Clinical Science)
  Mani Vembar



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