Toward patient-specific computational study of aortic diseases: a population based shape modeling approach

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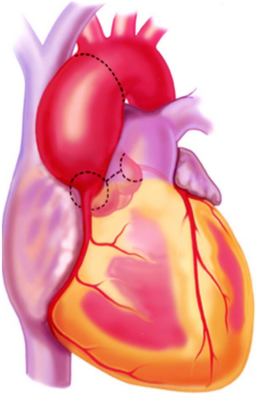
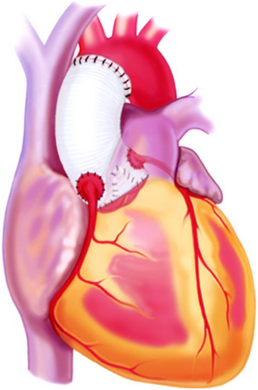
Outline

Traditional treatment: surgery



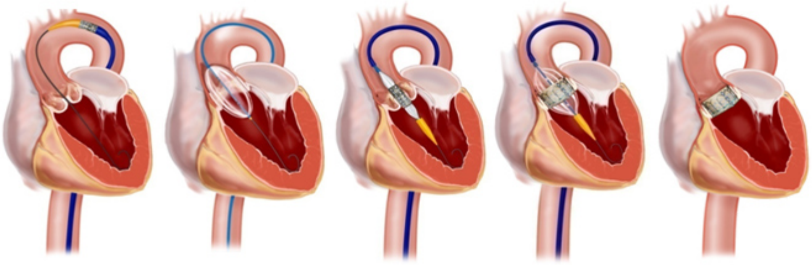
Before surgery (*AHA)



After surgery

- Cardiac aneurysm treated by prosthetic graft
- High risks for elderly and with concomitant issues

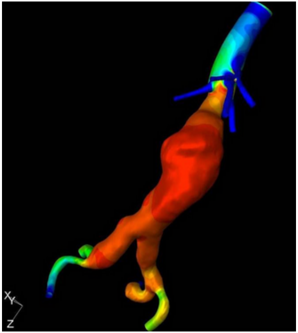
Alternative treatment



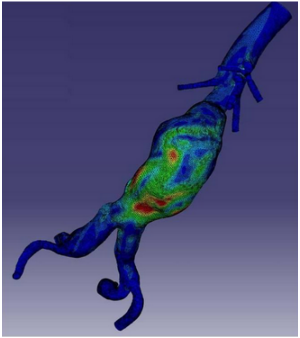
TAVR procedure (*Raney Zusman Medical Group)

- Transcatheter Aortic Valve Replacement (TAVR)
- Much lower risks than surgical replacement
- Challenge: success s.t. **aorta biomechanics** device shape, size, position and orientation etc.

Biomedical simulations



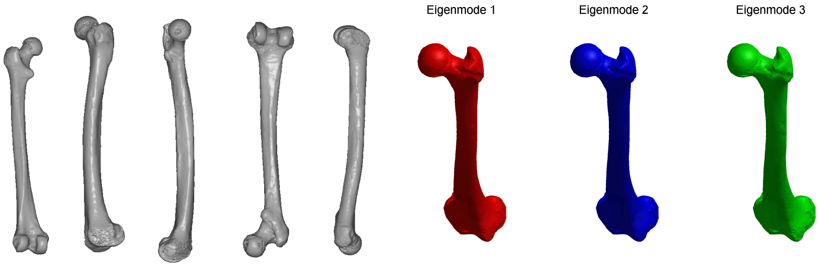
Fluid pressure (* Hazer, CMU)



Mechanical stress

- Numerical simulations: fast and inexpensive (FEM, CFD)
- Accuracy s.t. geometric modeling of aorta from CT/MRI
- Challenge: **patient-specific geometric modeling of aorta** time-consuming process, noisy and incomplete data

Statistical Shape Model



Patient data pool. e.g. femur SSM: mean + modes

- Promising solution: **Statistical Shape Model** (SSM)
  - Shape variation pattern in a population of shapes
  - SSM (mean + modes): a compact representation
- Patient-specific model easily constructed from SSM

Population based statistical shape modeling

- Formulated as an optimization problem
- Description length of statistical model defined by

$$f \doteq \sum_{m=1}^{n_S-1} L_m,$$

where each mode's contribution is

$$L_m = \begin{cases} 1 + \log(\lambda_m/\lambda_{\text{cut}}) & \lambda_m \geq \lambda_{\text{cut}} \\ \lambda_m/\lambda_{\text{cut}} & \text{otherwise} \end{cases}$$

- Optimization formulation

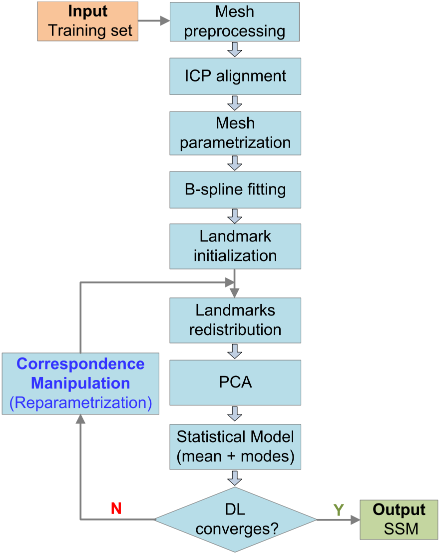
$$\min_{\mathbf{b}} \quad f(\mathbf{b}) = \sum_{\lambda_i \geq \lambda_{\text{cut}}} \left[1 + \log \frac{\lambda_k(\mathbf{b})}{\lambda_{\text{cut}}}\right] + \sum_{\lambda_k < \lambda_{\text{cut}}} \frac{\lambda_k(\mathbf{b})}{\lambda_{\text{cut}}} \tag{1a}$$

$$\text{s.t.} \quad \mathbf{E}(\mathbf{b})\ \mathbf{v}_k(\mathbf{b}) = \lambda_i(\mathbf{b})\mathbf{v}_k(\mathbf{b}) \tag{1b}$$

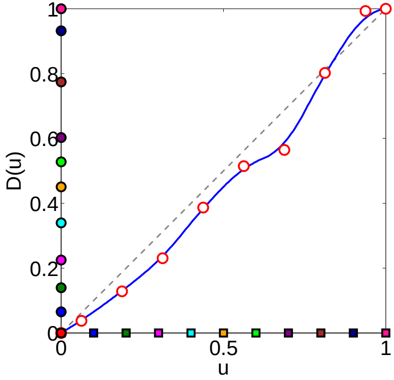
$$\mathbf{v}_k^T(\mathbf{b})\mathbf{v}_k(\mathbf{b}) = 1, \quad k = 1, ..., n_S \tag{1c}$$

$$g(\mathbf{b}) < 0 \tag{1d}$$

Aorta statistical shape modeling flowchart



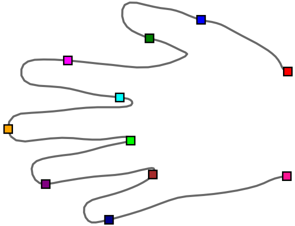
B-spline controlled landmarks manipulation



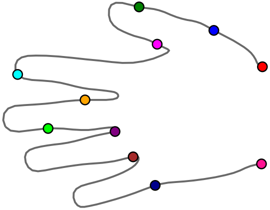
Reparametrization function $D(u)$

- Represented by B-spline

$$D(u) = \sum_{i=0}^{n_b-1} B_{i,p}(u) b_i$$

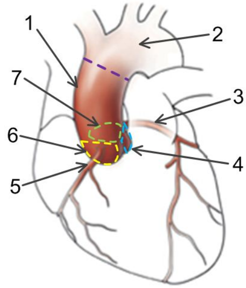


Before redistribution

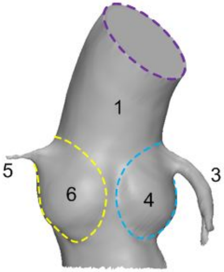


After redistribution

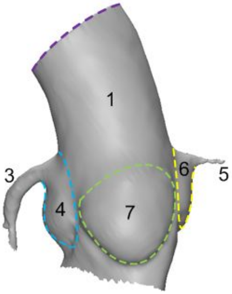
Aorta anatomy



Ascending aorta (anterior view)



Front view

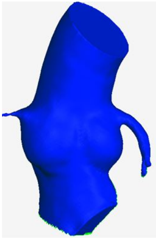


Back view

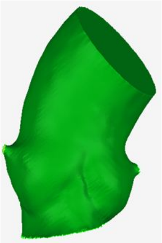
- 1) Ascending aorta; 2) Aortic arch;
- 3) Left coronary artery; 5) Right coronary artery;
- 4) Left coronary sinus; 6) Right coronary sinus; 7) Non-coronary sinus

Input raw triangle meshes

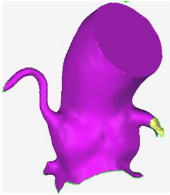
Shape 1



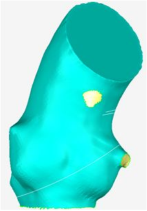
Shape 2



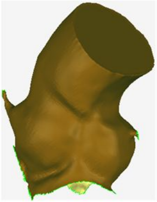
Shape 3



Shape 4



Shape 5

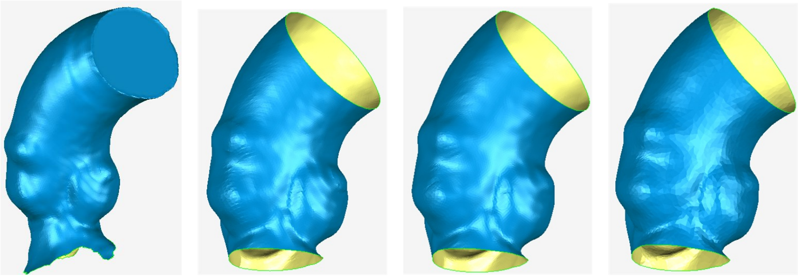


Shape 6

Shape	Patient	Sex	Age
1	A	M	44
2	B	M	42
3	C	M	59
4	D	M	37
5	E	M	45
6	F	M	49

- From CT images
- 6 patients
- Patient C with severe aneurysm

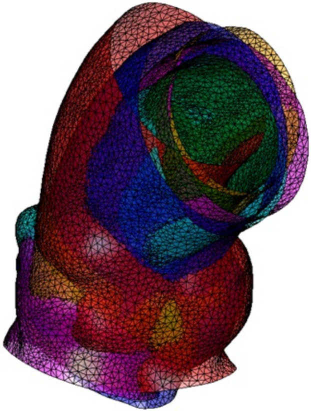
Mesh processing



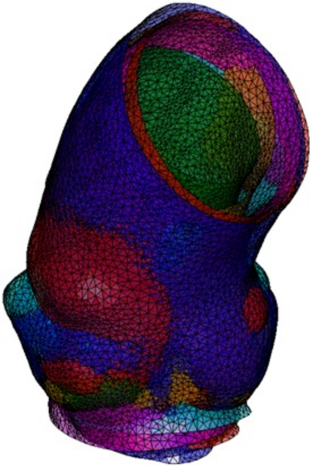
Hole filling | End trimming | Smoothing | Decimation

- Incomplete and/or noisy data
- Shape topology

One-time alignment



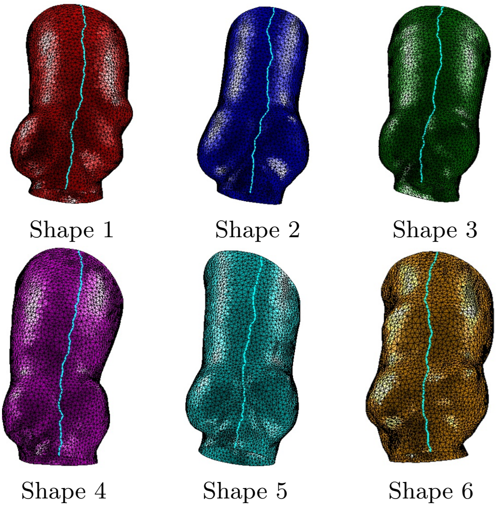
Before alignment



After alignment

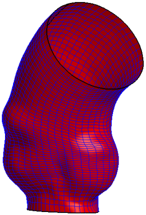
- Iterative Closest Point algorithm

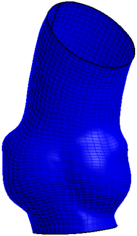
Generatrix construction

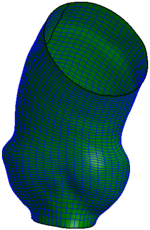


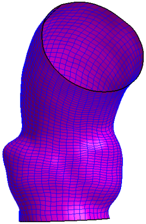
- Consistent cylindrical topology

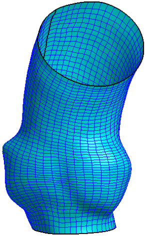
Training set B-splines fitting

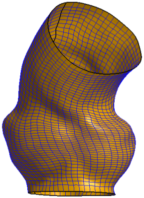

Shape 1


Shape 2

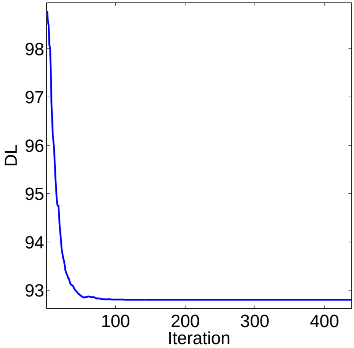

Shape 3


Shape 4

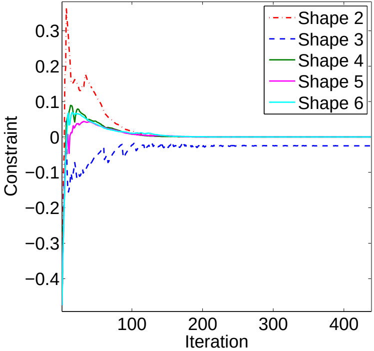

Shape 5


Shape 6

Optimization results



Objective function DL

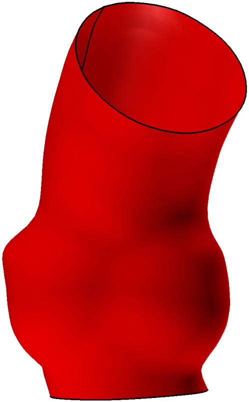


Constraints

- Objective (DL) drops from 98.77 to 92.80 in 439 iterations
- Optimized mode variations
  $\lambda_1 = 2.06$, $\lambda_2 = 0.44$, $\lambda_3 = 0.38$, $\lambda_4 = 0.21$, $\lambda_5 = 0.11$

SSM result: mode 1

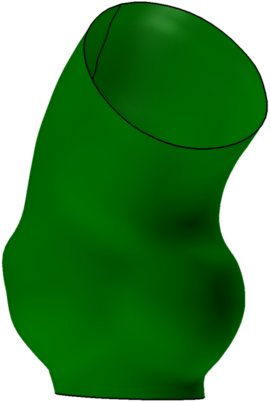
$$b_1 = -3.00\,\sigma_1$$



- Mode variation:
  $\lambda_1 = 2.06\ (64.5\%)$
- Standard deviation:
  $\Sigma_m = \sqrt{\lambda_m} \quad (m = 1, ..., 5)$
- Captured variation pattern:
  Ascending aorta dilation

SSM result: mode 2

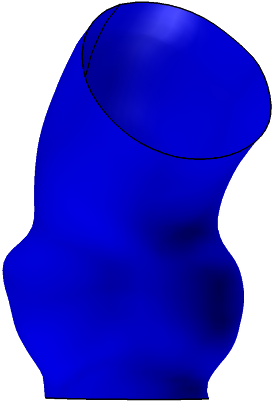
$$b_2 = -3.00\,\sigma_2$$



- Mode variation:
  $\lambda_2 = 0.44\ (13.8\%)$
- Accumulative percentage
  λ_1 & λ_2 = 78.3%
- Captured variation patterns:
  Ascending aorta dilation
  Coronary sinus dilation

SSM result: mode 3

$b_3 = -3.00\,\sigma_3$



- Mode variation: $\lambda_3 = 0.38\ (11.8\%)$
- Accumulative percentage λ_1 & λ_2 & λ_3 = 90.1%
- Captured variation patterns:
  Ascending aorta dilation
  Coronary sinus dilation
  Annulus dilation

Patient-specific modeling from SSM

- Problem statement
  - Input 1: SSM = mean $\bar{\mathbf{x}}$ + modes $\{\mathbf{v}_m\}$
  - Input 2: any patient shape data $\mathbf{S}_{\text{Patient}}$
  - Output: Patient specific model $\mathbf{x}_{\text{Patient}} = \bar{\mathbf{x}} + \sum_{m=1}^{\widetilde{m}} \beta_m \mathbf{v}_m$
  - Find $\{\beta_m\}$ s.t. $\mathbf{x}_{\text{Patient}}$ sufficiently represents $\mathbf{S}_{\text{Patient}}$
- Viable methods
  - Direct projection $\mathbf{x} \approx, \ \beta_m = (\mathbf{x} - \bar{\mathbf{x}})^T \mathbf{v}_m$
  - Shape fitting. e.g. ICP etc.
- Advantages
  - More efficient, more convenient
  - Less risky, less costly
  - Less subject to incomplete data and/or feature noise

Conclusion

- Biomedical simulation: promising alternative to aorta surgeries
  - Advantage: much lower risks
  - Challenge: patient-specific geometric modeling of aorta
- Proposed solution: population based statistical shape modeling
  - Characterizes shape variation patterns in a set of shapes
  - Formulated as a optimization problem
  - Aorta variation across patients captured by statistical modes
  - Easy construction of patient-specific aortic model
- Future work
  - More complex topology
  - Larger population of aorta