Statistical shape model of aneurysmal abdominal aorta

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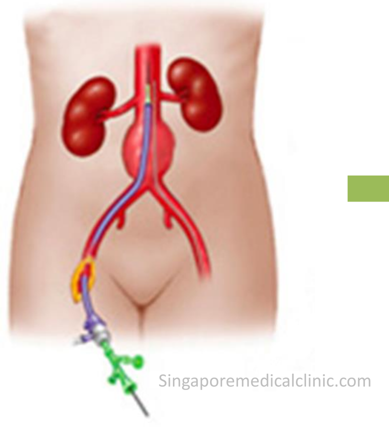
Context & Objectives

Endovascular treatment

Introduction of medical devices through tortuous iliac arteries to reach the lesions (e.g. abdominal aortic aneurysm, aortic valve stenosis)



Need to optimize the endovascular treatment to avoid complications

Population with abdominal aortic aneurysm (AAA)

Large morphological variability

Analyze the population

Statistical Shape Modelling

- Allows to capture the morphological variability in a population
- Recently reported works:
  - Human nasal cavity (Keustermans et al, 2018)
  - Femur (Gaffney et al, 2019)
  - Healthy thoracic aorta (Wörz et al, 2015; Casciaro et al, 2013)

Objective:

Development of a Statistical Shape Model of aortoiliac anatomies with AAA

Method

Dataset

556 preoperative CT scans of patients suffering AAA

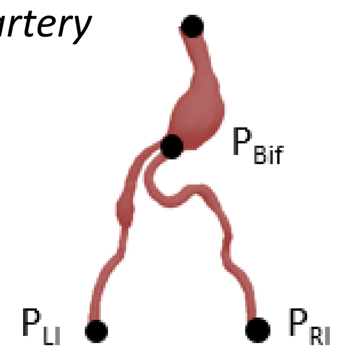
Centerline computation

Preoperative CT scan

EndoSize®

3D Vascular geometry + Anatomical Points

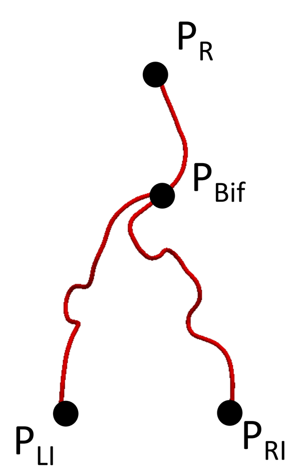
P_R : *Below the lowest renal artery*



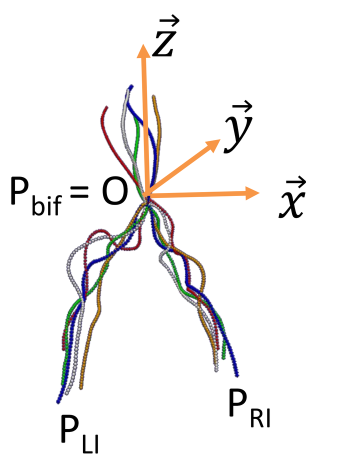
Before the bifurcation with the superfical artery

VMTK

Centerline (CL)



Learning dataset = isotopological CLs



- Each branch of the CL is discretized with 80 points.
- A translation is applied so that P_{Bif} is at the center of the coordinate system (O, $\vec{x}$, $\vec{y}$, $\vec{z}$).
- A rotation of center O around $\vec{z}$-axis is applied so that P_{RI} is in the plane *y = 0*.
- $\vec{z}$-axis (patient craniocaudal axis) is unchanged

For a patient i, the vector L_i represents the isotopological CL

Statistical Shape Model

$P = [L_1 \;\; \dots \;\; L_m]$ → Singular Value Decomposition → $P = M\,S\,V^T$

- the columns of *M* are the left unit singular vector → **modes**
- the columns *V* are the right unit singular vector
- *S* the diagonal matrix composed of the *m* singular values of *P* listed in descending order

L^*: New isotopological CL → Projection in the basis of modes : $\alpha = M^T \cdot L^*$

$\tilde{L}^*$: approximated CL by r modes (r << m) $\tilde{L}^* = \sum_{k=1}^{r} M_k \alpha_k$

Results

Modes

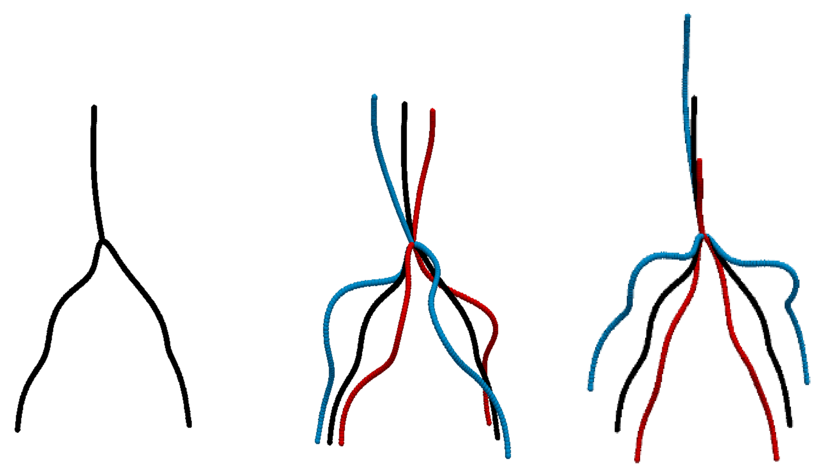
Mean CL given by the 1st mode

$CL_{\text{mean}} = mean(\alpha_1)\; M_1$

Limits of the range of deformation induced by the mode *i*

$CL_{\max}(i) = CL_{\text{mean}} + \max(\alpha_i)\, M_i$

$CL_{\min}(i) = CL_{\text{mean}} + \min(\alpha_i)\, M_i$

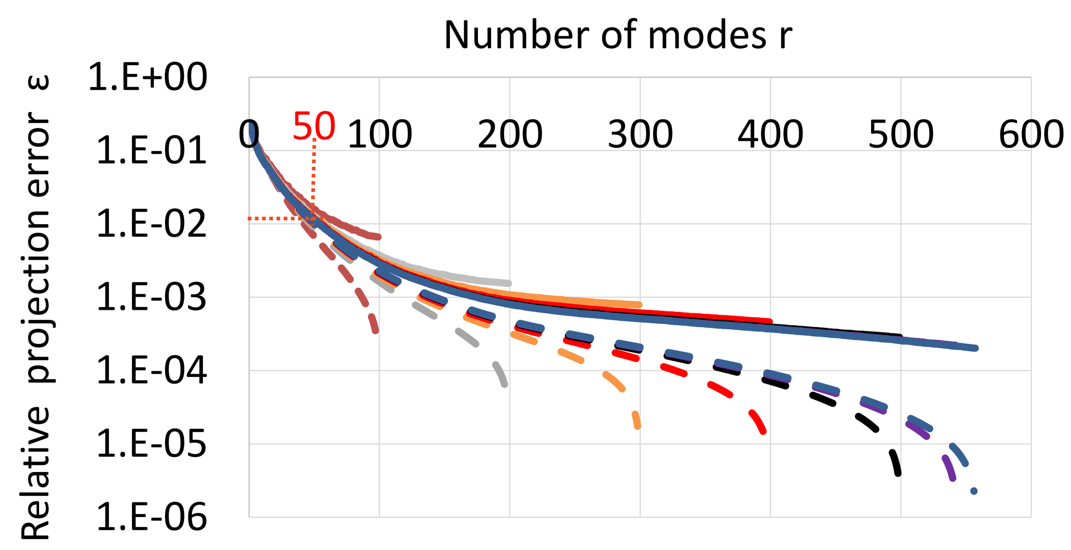


***Mode 1** (Mean CL) **:** iliac arteries slightly tortuous*

***Mode 2 :** complex deformation of the iliac arteries and inclination of the abdominal aorta*

***Mode 3** influences the iliac tortuosity and the distance between P_{Bif} and the boundary points (P_R, P_{LI}, P_{RI}).*

Accuracy



- - - ε_{in}: error due to the approximation with *r* modes obtained by projecting the *CLs* in the learning dataset considering a basis of *r* modes.

—— ε_{out}: error between the removed *CL* L_i approximated by $\tilde{L}_i$ in the basis of *r* modes (leave-one-out approach)

To represent accurately a CL external to the learning dataset:

A relatively high number of modes (50 modes) must be considered

A large learning dataset is necessary

Conclusion & Perspectives

Possible to accurately represent sick vascular structures

- Take into account the radius variation along the CL
- Understand shape variation in the pathological population

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