conference VPH2026

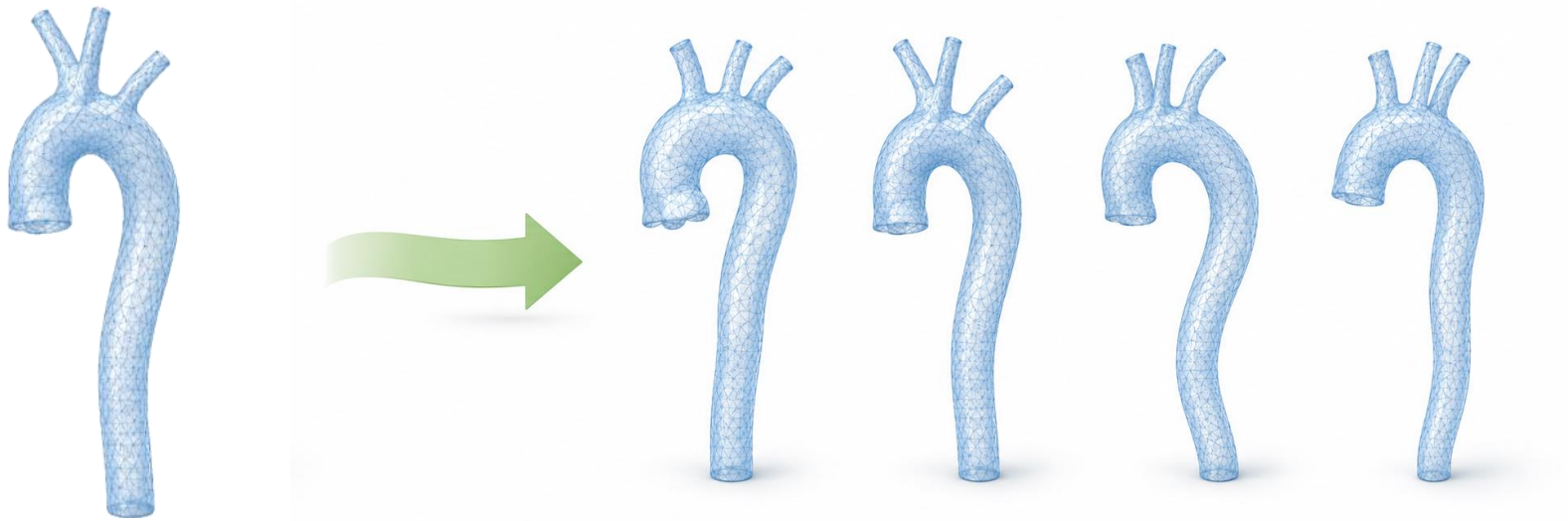
TOR VERGATA
UNIVERSITÀ DEGLI STUDI DI ROMA

AN RBF-BASED FRAMEWORK FOR GEOMETRIC CONTROL OF CARDIOVASCULAR STATISTICAL SHAPE MODELS

International Conference on the Virtual Physiological Human, Milan, 02-09-2026

Authors: Andrea Baldini, Leonardo Geronzi, Marco Evangelos Biancolini

Introduction



Statistical Average Model

Fails to capture critical anatomical extremes

Statistical Shape Model

Captures the full spectrum of population variability

Synthetic Datasets

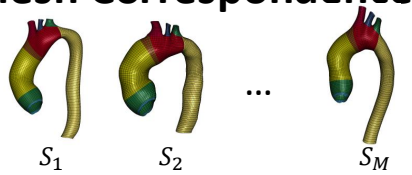
- Systematic generation of massive virtual cohorts
- Enables exploration of rare morphologies and pathological states beyond the limitation of scarce datasets

R&D Impact

- Population-level analyses based on in-silico simulations
- Testing implants on thousands of varied synthetic geometries before physical trials

Statistical Shape Models

1 Mesh Correspondence



2 Vectorization

$$s_i = [x_1, y_1, z_1, \dots, x_n, y_n, z_n] \in \mathbb{R}^{3n}$$

3 Centered Data Matrix

$$X = \begin{bmatrix} (S_1 - \bar{S})^T \\ \vdots \\ (S_M - \bar{S})^T \end{bmatrix}$$

4 SVD/PCA

$$X = USV^T$$

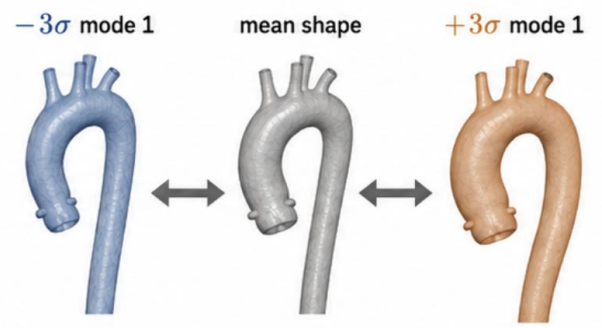
$$s(\alpha) = \bar{s} + \sum_{k=1}^{K} \alpha_k \sigma_k \boldsymbol{v}_k$$

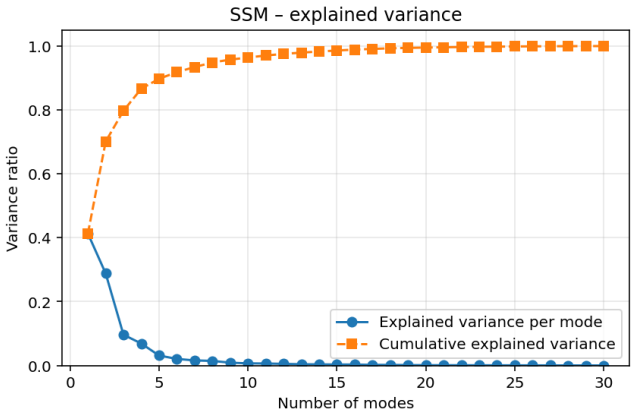
$\boldsymbol{v}$ Columns of $\boldsymbol{V}$ = shape modes (orthonormal basis in shape space)

$\boldsymbol{\sigma_k}$ Singular values (shape scales)

$\boldsymbol{\alpha_k}$ Low dimensional coordinates (shape parameters)

$$\boldsymbol{dim(\alpha) = K \ll M}$$





SVD provides an orthonormal basis of shape modes **V** ranked by explained variance λ_k.
Any new shape can be represented compactly by the coefficients $\boldsymbol{\alpha}$.

Limitations of Singular Value Decomposition

Standard SVD-based SSM

- Clinically Opaque: statistical bases lack clinical meaning.
- Global Entanglement: Unpredictable whole-shape deformation
- Requires expert knowledge

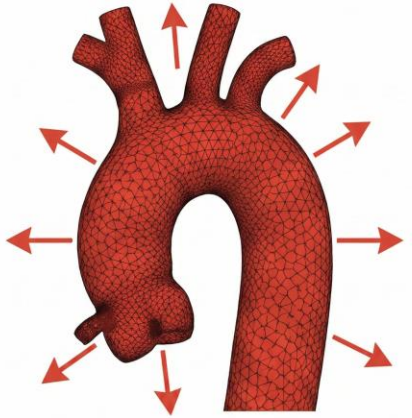
Descriptor-Driven Deformation

- Clinically meaningful: 1:1 mapping to clinical metrics.
- Local: Targeted changes
- User-Friendly: designed for non-experts

Standard SVD control

Mode 1

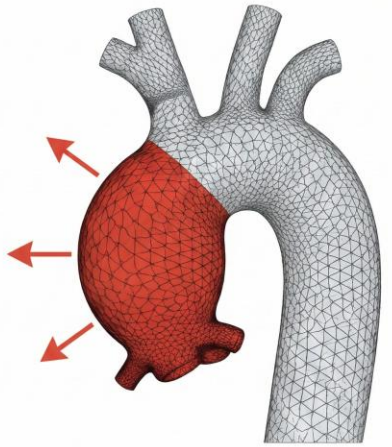
$-\sigma$ $+\sigma$



Descriptor-driven control

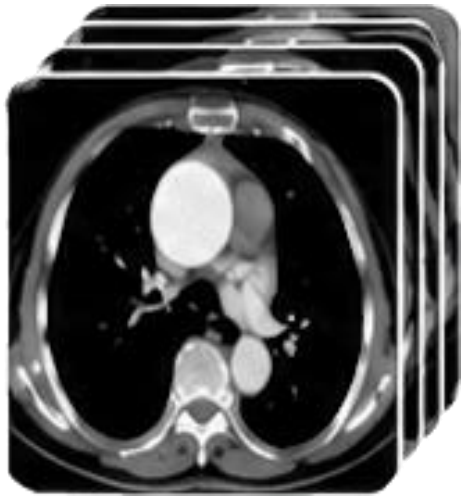
Ascending Diameter

$30mm$ $55mm$



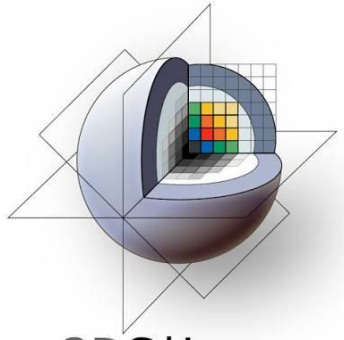
Methods: Dataset & Feature Extraction

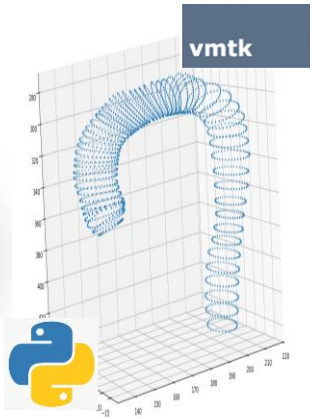
INPUT DATA

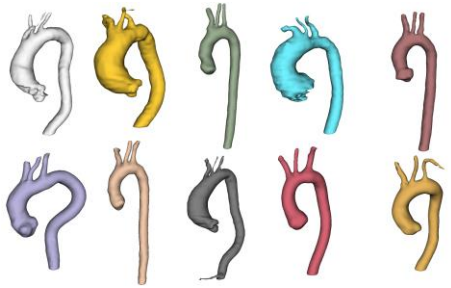


TotalSegmentor Dataset
Raw CT scan
N=61

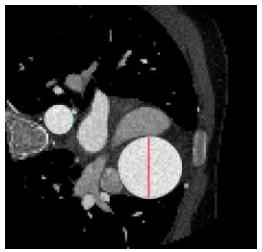
DATA PROCESSING
VENUS X







Segmentation



Feature Extraction

OUTPUT FEATURE VECTOR

$\boldsymbol{x} \in \mathbb{R}^5$

Diameter Characterization

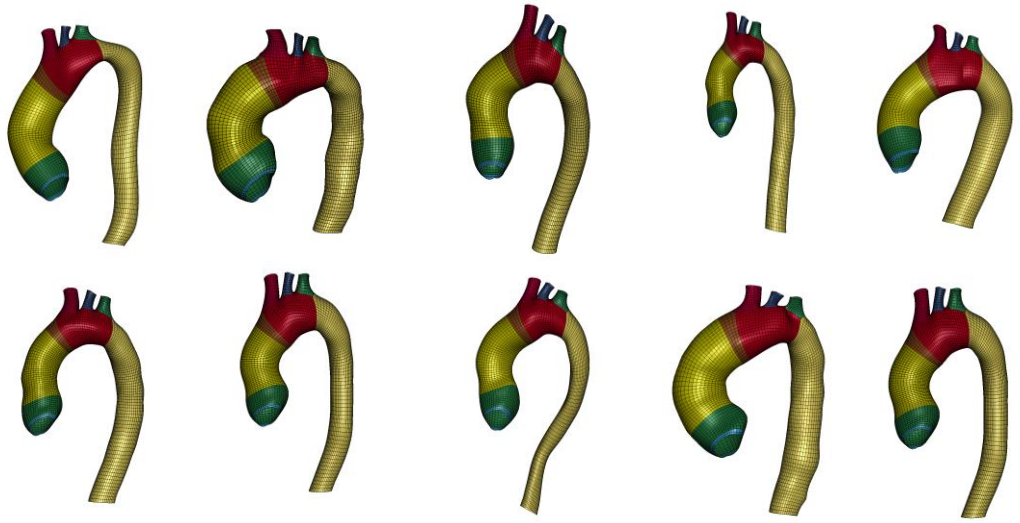
1. *Max Ascending Diam.*
2. *Max Arch Diam.*
3. *Max Descending Diam.*

Global Descriptors

1. *Centerline Length*
2. *Tortuosity*

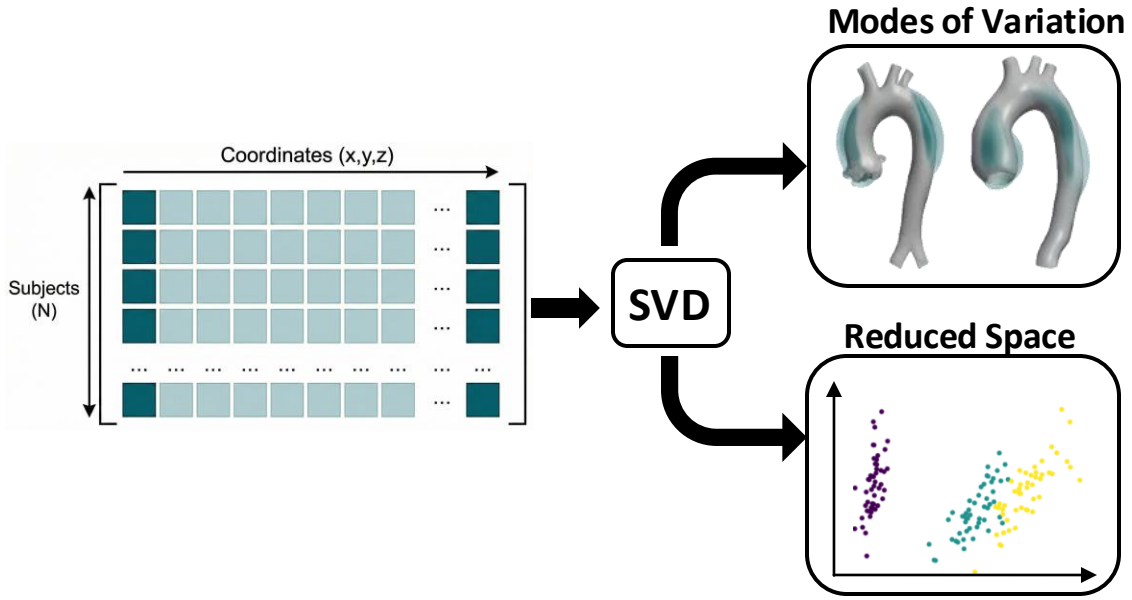
Methods: Statistical Shape Modeling

Iso-Topological Mesh Generation (Morphing)



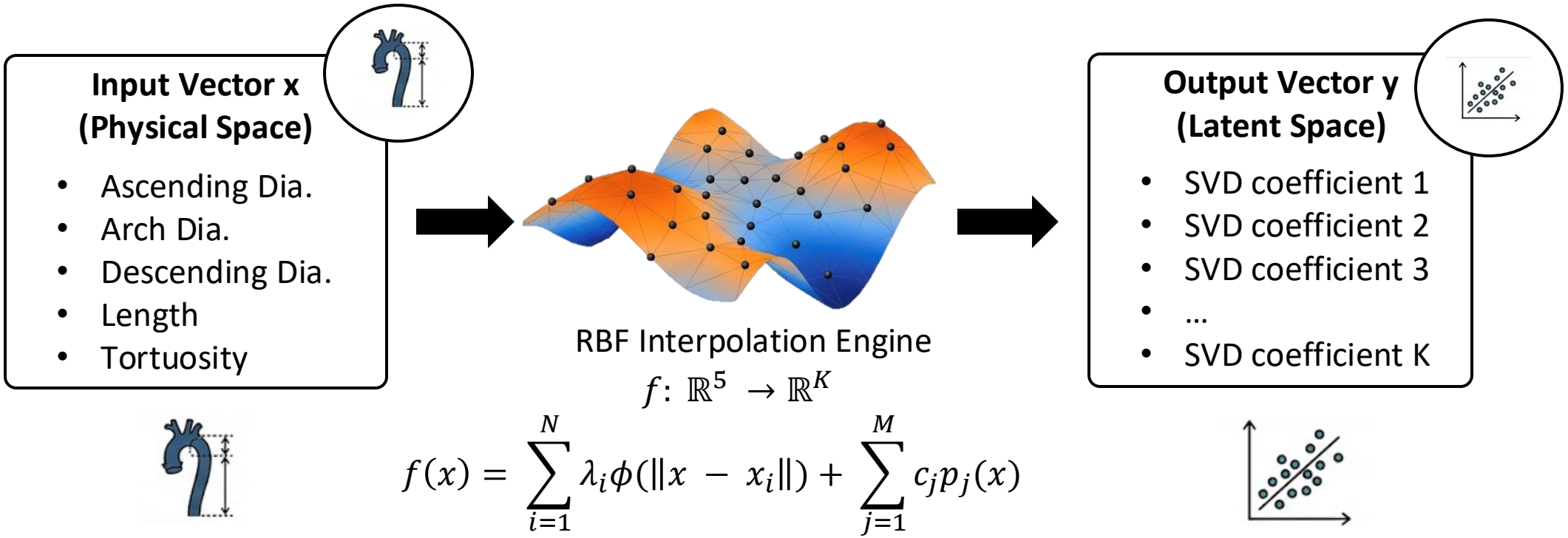
- **Reference Mesh**: Median Anatomy baseline (6226 nodes)
- **Alignment**: Rigid alignment to common reference frame
- **RBF morphing**: Radial Basis Function deformation to guarantee iso-topology
- **Refinement**: final projection onto the target mesh

Statistical Shape Model Construction



- **Vectorization**: Dense vectors of (x, y, z) coordinates
- **SVD**: Extraction of orthonormal modes to capture variability
- **Dimensionality Reduction**: Top K modes retained to account for ~95% of population variance

Methods: Physical-To-Latent Surrogate Mapping



Key Features

- Radial Basis Function Interpolation selected for its ability to handle scattered data in high-dimensional space.
- For each SVD mode k, a dedicated RBF interpolant was trained to predict the coefficient required to match the input parameters
- Z-score normalization applied to inputs to ensure isotropy

Methods: Surrogate Mapping Validation

Input Descriptors

$$x_{target} = \begin{bmatrix} D_{asc} \\ D_{arch} \\ D_{esc} \\ T \\ L \end{bmatrix}$$

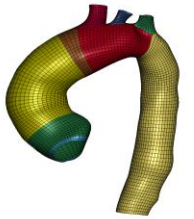
1. Prediction

Predicted Latent Coefficients

$$\hat{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_K \end{bmatrix}$$

2. Reconstruction
(SVD Inverse: $\hat{s} = \bar{s} + \phi\hat{y}$)

Reconstructed Geometry ($\hat{s}$)



3. Measurements & Comparison

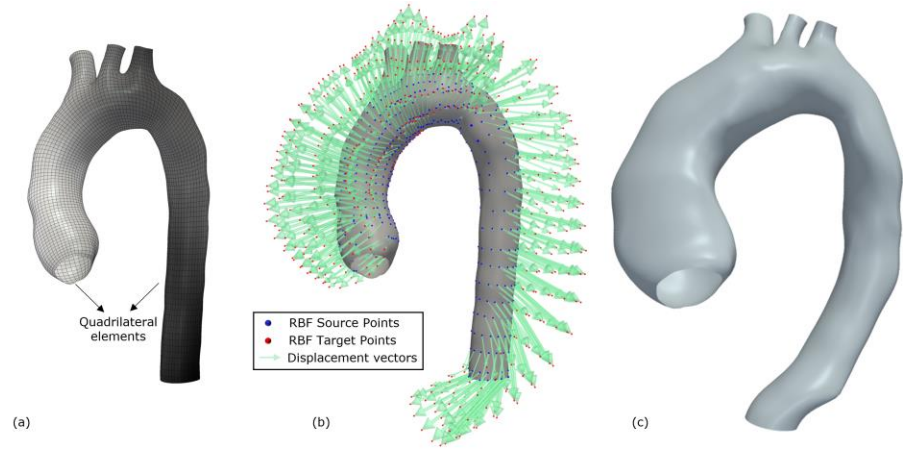
Error quantification (RPE)

$$RPE_j = \frac{|x_{measured,j} - x_{target,j}|}{x_{target,j}} \times 100$$

Compare Measured vs. Target Descriptors

***Validation Set**: 16 distinct anatomical configurations covering design space variability

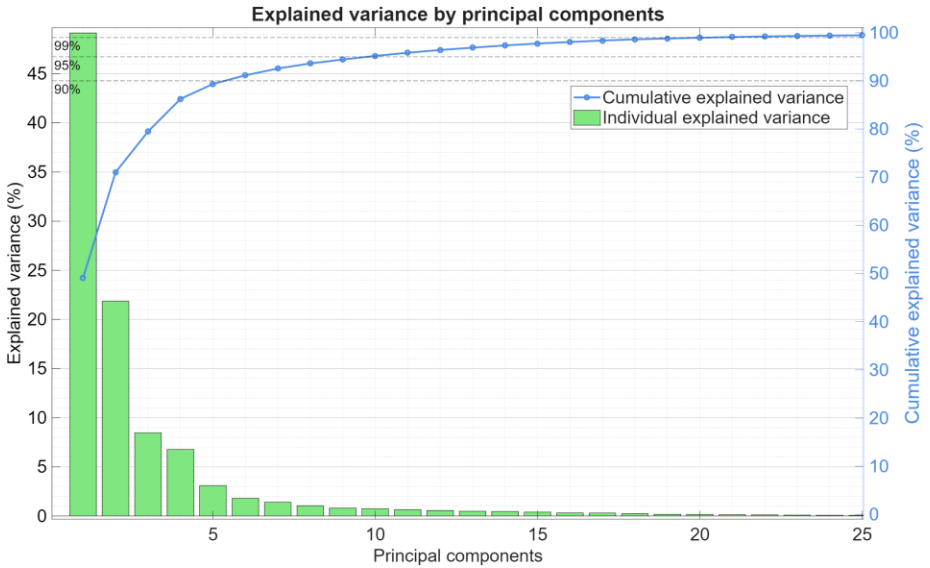
Results: Statistical Shape Modeling



Mesh Morphing & Topology

Data Processing: N=61 thoracic aortas successfully segmented

Result: 100% nodal correspondence (iso-topology) across the cohort



Dimensionality Reduction

Anatomy S approximated as: $\boldsymbol{s} \approx \bar{\boldsymbol{s}} + \boldsymbol{\phi y}$

Variance Analysis: The first 10 modes capture 95% of the total anatomical variability

This creates a compact, low-dimensional latent space

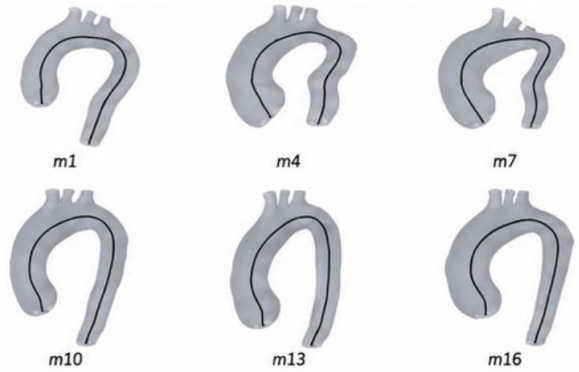
Results: Geometric Consistency

Relative error heatmap [%]

	D_{asc}	D_{arch}	D_{desc}	L	T
m1	2.1	3.8	5.6	2.4	8.7
m2	1.7	0.1	0.8	5.8	1.4
m3	4.7	5.1	12.5	5.5	5.7
m4	14.0	4.0	3.1	12.1	4.4
m5	5.5	14.0	11.3	7.0	4.2
m6	3.6	3.4	0.5	13.5	3.2
m7	0.1	9.5	0.5	9.4	5.2
m8	8.4	0.3	1.0	9.3	0.6
m9	0.7	2.3	9.3	2.5	1.8
m10	1.9	1.1	11.0	1.2	1.7
m11	0.2	1.5	12.0	8.5	0.5
m12	0.4	4.7	14.9	9.9	0.4
m13	0.7	2.2	3.7	8.4	0.8
m14	1.2	3.0	6.3	6.1	1.1
m15	7.5	0.7	2.2	3.8	0.1
m16	5.1	2.7	2.5	2.7	0.7

Largest deviations were observed for D_{desc} and L

Representative Cases



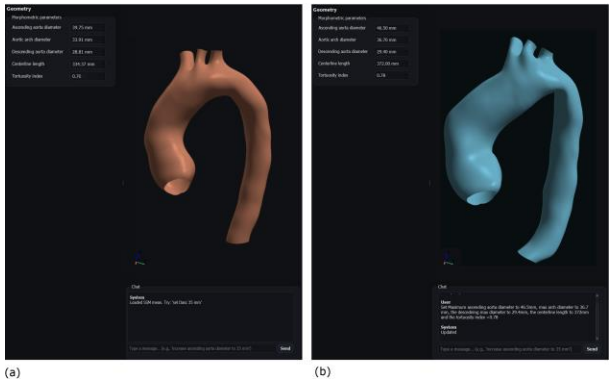
- **Avg Relative Percentage Error:** $4.5\% \pm 4.0\%$
- **Precision:** Sub-millimetric (<0.5mm) for most diameters' configurations
- **Stability:** Ascending/Arch Diameters < 5% error. Descending diameter median error < 7%

Closed-loop reconstruction remains geometrically stable across diverse synthetic anatomies

Natural-language control of an RBF-driven aortic shape model

The RBF layer establishes an explicit and deterministic bridge between anatomical intent and the PCA latent space, translating user-defined shape changes into the modal coefficients required to update the 3D geometry. This enables a new form of **parametric CAD** in which the aortic geometry can be controlled through natural language.

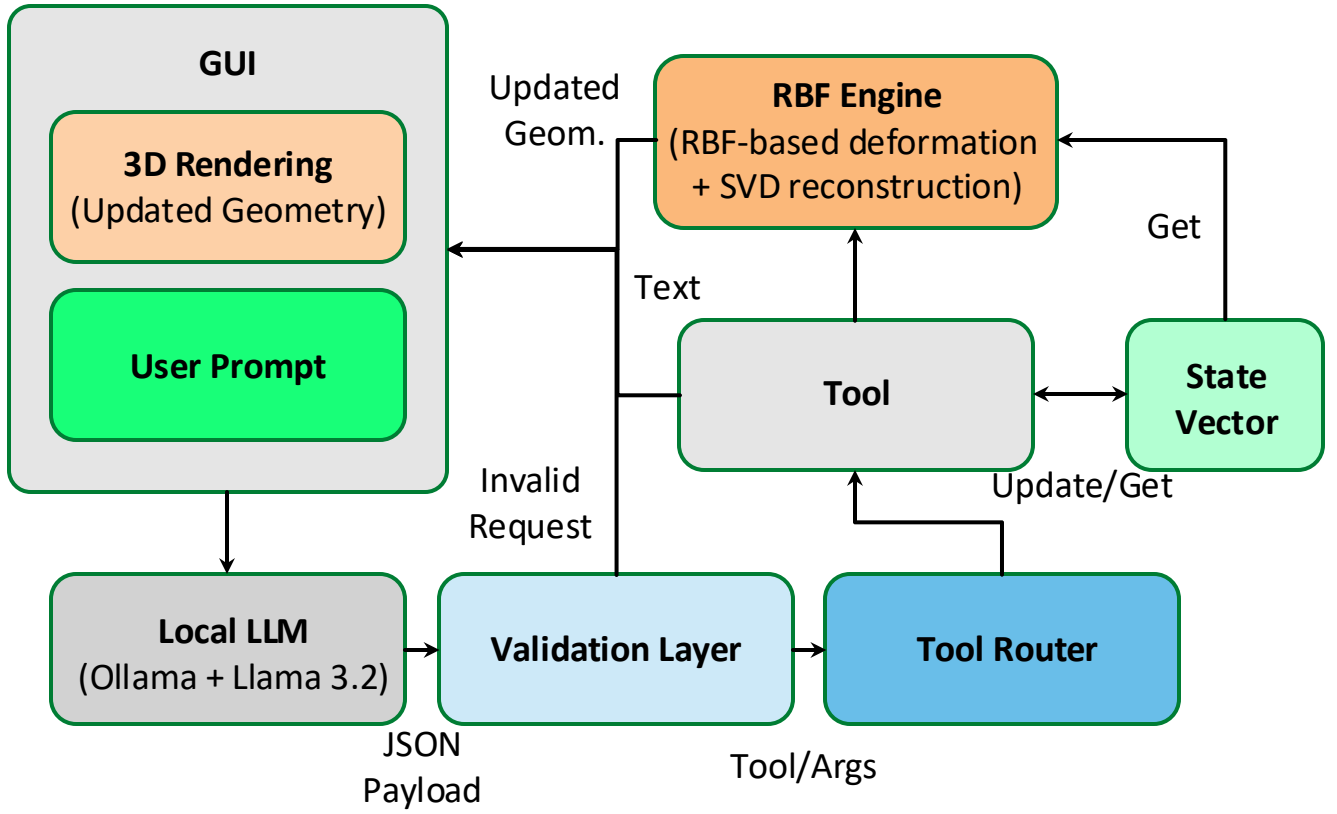
User Input



Real-Time visual feedback of updated geometries and system status

- Current shape preview
- Parameter values
- System messages

Closed-Loop Interactive Architecture (RBF-enabled)



Conclusions and Implications

1. Core Contributions

- Transform SVD-based SSM latent space into an interpretable descriptor space
- Deterministic RBF mapping links shape coefficients to 5 anatomical descriptors
- Avoids trial-and-error tuning of abstract modes
- First use case: natural language control of RBF-driven aortic geometry

2. Key Validation Results

Closed-loop MRPE	$4.5\% \pm 4.0\%$
Diameter validation error	$< 0.5mm$

3. Clinical/Research Utility

- Intuitive generation of synthetic aortic cohorts
- Supports in-silico device trials
- Bridges clinical intent and computational modelling

4. Next Steps

- Expand beyond N=61 subjects
- Psychometric test for application acceptance
- Extent to abdominal aorta, heart and other organs

THANK YOU FOR YOUR ATTENTION

Speaker: Andrea Baldini

Email: andrea.baldini@uniroma2.it

Authors: Andrea Baldini, Leonardo Geronzi, Marco Evangelos Biancolini