Uncertainty Quantification in Patient-Specific Cardiovascular Simulation for Enhanced Health Monitoring and Treatment Planning

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INTRODUCTION

Patient-specific cardiovascular simulation

Patient-specific cardiovascular simulations enable non-invasive assessment of hemodynamics in heart and major blood vessels for patients suffering from cardiovascular disease. This data is not readily available from standard clinical measurements, yet it can offer key insights into disease progression and subsequent physiologic response, and thus aid in surgical and treatment planning and clinical decision-making [1].

Importance of uncertainty quantification

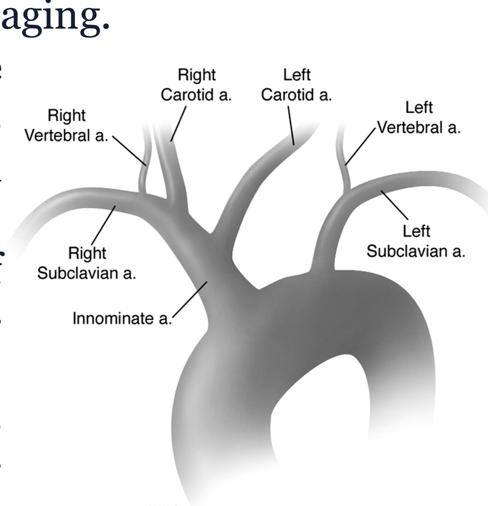
The confidence in the data output from cardiovascular simulations depends directly on our level of certainty in simulation input parameters. The sources of uncertainties in cardiovascular simulation include clinical data, geometry, boundary conditions, material properties, and simulation parameters. In a variety of situations, the simulation outputs are quantified only probabilistically due to presence of noise in input data. Simulations are only as accurate as the data that goes into them and a thorough study is needed to determine how variations in these input data affects the outputs. In addition, when evaluating new surgical designs, we need to ensure that changes due to design parameters are larger than noise caused by input uncertainties. Therefore, patient-specific computational simulations need to be performed over a set of fuzzy parameters to determine how robust simulation outputs are to variation in input parameters.

OBJECTIVE

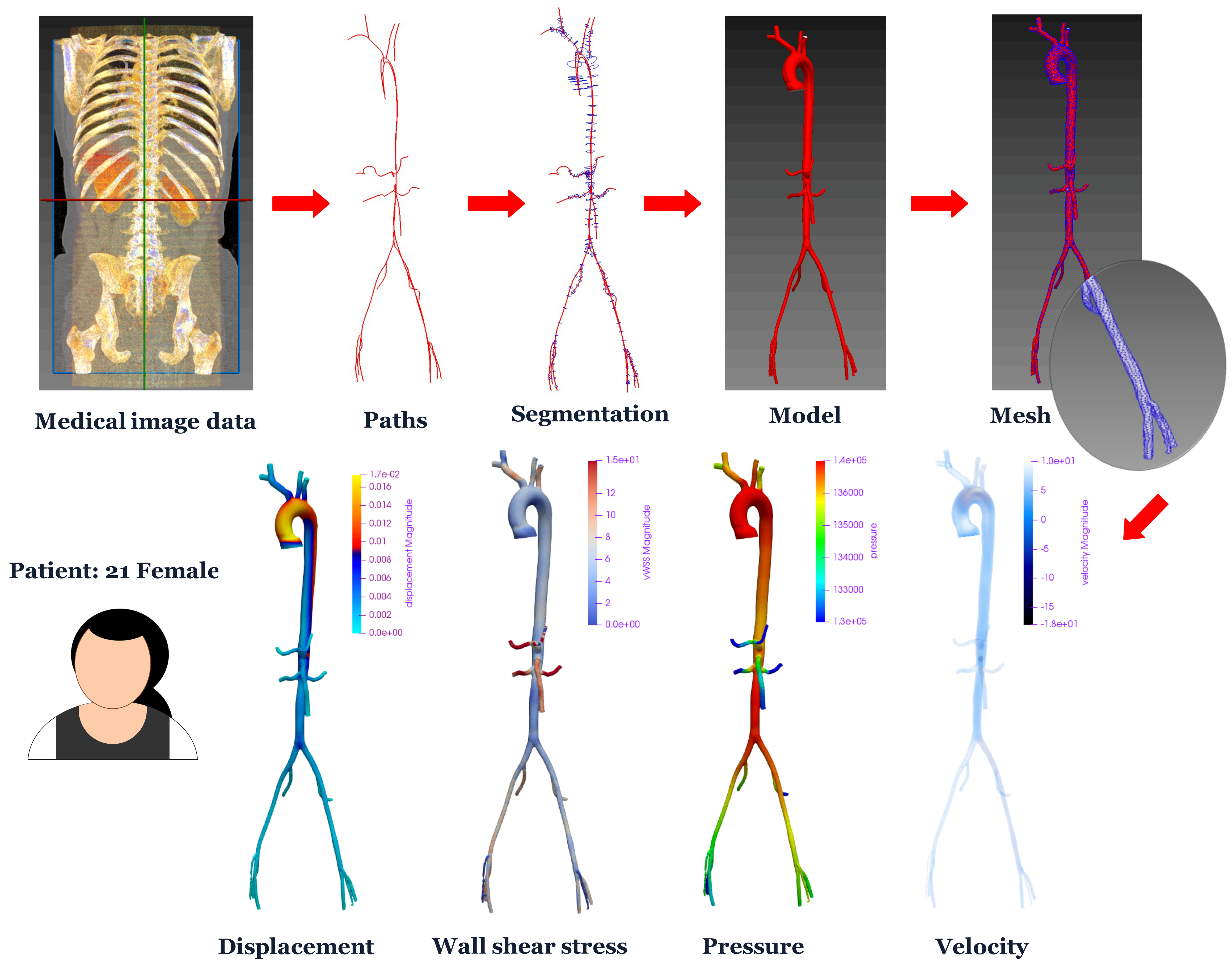
We perform uncertainty quantification using Polynomial Chaos Expansion (PCE) to evaluate the sensitivity of output parameters to input uncertainties in patient-specific cardiovascular simulations. Specifically, we study the uncertainty in flow properties in left and right common carotid arteries, due to the uncertainties in the stiffness and thickness of aortofemoral system. Common carotid artery volume flow rate and pressure is clinically useful for study of cerebrovascular disease [2].

Arterial stiffness is often approximated by measuring pulse wave velocity or by analyzing local variations in local pressure and volume [3]. Arterial wall thickness can be approximated using ultra sound tests [4]. Arterial stiffness and thickness may vary patient by patient, and changes by medicine, and due to aging.

Based on the literature, we assume aertofomeral thickness and elasticity modulus follow a uniform probability distribution with variabilities in the ranges of 1.2817-2.7183 mm and 100,000-50,000,000, respectively [4,5]. The cardiovascular simulation is performed using simvascular [1,6].



PATIENT-SPECIFIC CARDIOVASCULAR SIMULATION



METHODOLOGY

Polynomial Chaos Expansion (PCE) is a mean to assess how the uncertainties in a model inputs manifest in its outputs. It ca be much more efficient than Monte carlo methods. Call the uncertain inputs $\boldsymbol{\xi}$ and the output φ. Uncertainty of $\boldsymbol{\xi}$ is specified via its pdf $\rho(\boldsymbol{\xi})$. We seek for the pdf of φ or at least information about how it varies as $\boldsymbol{\xi}$ varies.

The basic idea is to express the output as a polynomial series:

$$\varphi(\boldsymbol{\xi}) = \varphi_0 + \varphi_1 P_1(\boldsymbol{\xi}) + \varphi_2 P_2(\boldsymbol{\xi}) + \ldots$$

The orthogonal polynomials P_k are related to pdf ρ:

$$\int P_j(\boldsymbol{\xi})\, P_k(\boldsymbol{\xi})\, \rho(\boldsymbol{\xi})\, d\,\boldsymbol{\xi} = \delta_{j,k}$$

Coefficients φ_0 , φ_1 , … can be estimated using least squares, stochastic collocation, or stochastic Galerkin approaches.

RESULTS

Using the results from 25 simulations and the least squares, six different 4th degree PCEs are constructed for flow rate and pressure in left and right common carotid arteries.

Flow statistics in left common carotid artery

	Q_{avg}(L/m)	P_{avg}(mmHg)	P_{max}(mmHg)
Mean	0.3373	97.5326	102.2925
STD	0.0018	1.0353	0.0650

Flow statistics in right common carotid artery

	Q_{avg}(L/m)	P_{avg}(mmHg)	P_{max}(mmHg)
Mean	0.3378	97.4158	102.1556
STD	0.0011	0.9768	0.0604

FUTURE WORK

By using patient-specific medical data, we can perform patient-specific Bayesian parameter estimation:

1. Collect clinical patient-specific images and data

SimVascular

2. Construct a patient-specific computational model (paths, segmentation, modeling, and mesh generation)

python

3. Sample from simulation parameters prior distributions

SimVascular

4. Solve the Navier-Stokes equations

python

5. Perform a forward model evaluation using PCE surrogate (calculate likelihood function using results and observed data)

python

6. Repeat steps 3-5 with a new set of parameters, continue until convergence

CONCLUSION

- Our end goal is to build patient-specific models that account for the uncertainties and errors inherent in the data and simulation.
- The Bayesian inference can be used to estimate probabilistic parameters given patient-specific medical data
- We developed a fast surrogate to speed up probabilistic simulations and consequently parameter estimation.

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