

Master's Thesis
Deep Iliac:
Learning Biomechanical Fluid-Structure-Interaction
in the Iliac Bifurcation

Lead Project Aortic Dissection

Graz Center of Computational Engineering

Initiative Lead: Institute of Theoretical Physics and Computational Physics, TU Graz

Involved Partners:

Institut für Mathematik, Lehrstuhl Wissenschaftliches Rechnen, Universität Augsburg

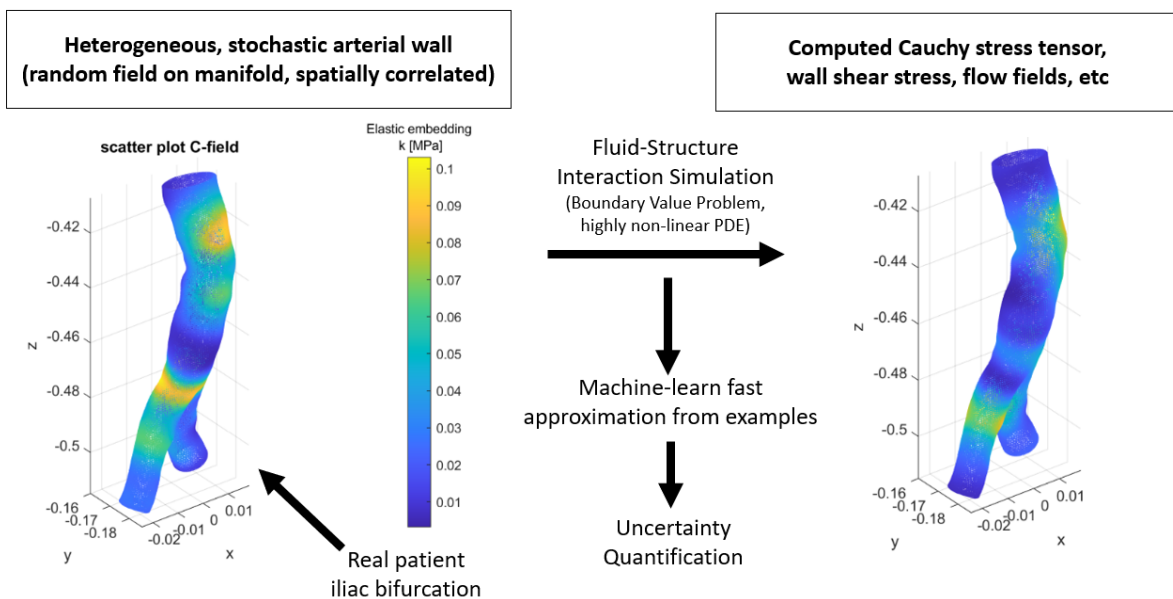
Institut für Biomechanik, TU Graz

Institute for Structural Analysis, TU Graz

Institute of Computer Vision and Computer Graphics, TU Graz

Medical doctors base their decisions on experience and intuition. For patients with life-threatening diseases of the arteries, such as aortic dissection, a decision pro surgery is not made easily since such a surgery is extremely difficult and of high risk. If mechanical stresses in the arteries are computed, then the disease's progression could be predicted, and thus medical doctors could make better, possibly life-saving decisions. To compute the mechanical stresses, we need the mechanical properties of the patient's tissue, yet the exact properties of the tissue are typically unknown. For example, the stiffness of arterial walls shows a large variation with respect to age, gender and lifestyle of the patient. In that sense, the stiffness is handled mathematically as a Random Variable. In addition to that, the stiffness shows a large variation within the patient itself. I.e., the arterial wall stiffness is highly heterogenous, and quite different in the thorax (upper body) and abdomen (lower body). Thus we need to extend the mathematical formulation from Random Variables to Random Fields. These Random Fields deliver data that shows a high degree of structure, e.g. in 2-dimensions it can be represented by a picture. Here, we will look at the iliac bifurcation of the abdominal aorta (see figure below) into the femoral arteries, i.e. the random field lives on a 2D-manifold in 3D space, where the domain is discretized in structured hexahedra yet the manifold discretization is generally irregular. It is exactly the structure in the data that is a prerequisite for modern applications of convolutional neural networks, e.g. face recognition. In this Master's Thesis, a Random Field will be the input parameter field to Partial Differential Equations derived from Continuum Mechanics for Arterial Walls, the solution of which is then a transformed Random Field again. The predictions of mechanical stresses in the arterial walls could then serve cardiovascular surgeons in their decision making. To quantify the salient uncertainties in these predictions, we need to solve the PDEs many million times. Since this is entirely impossible with brute force, we will make use of approximations in which machine learning techniques play a central role. I.e. PDE solutions will be learned from examples, the so constructed surrogate then used to compute the marginal probability density functions in the observables. Promising approaches are Riemannian/geodesic convolutional neural networks (possible alternative are normalizing flows, with point-wise Gaussian process regressors as minimum fallback safe-guards). The physics to be machine-learned is highly non-trivial. The solid (i.e. arterial wall) is non-linear and non-rigid, the fluid (i.e. blood) is non-Newtonian, and the interaction between the two is non-trivial. Departing from the previous pilot study [1] (published in the best journal in the field!), in this project we will look in particular at the random interaction between the viscoelastic embedding of the organ (the "suspension" that keeps the innards in place) in opposition to the hyperelastic constitutive model of the wall. The constitutive model is build and informed by experimental data acquired from the Institute of Biomechanics [2], the Fluid-Structure-Interaction solver [3,4] is then implemented in ExaDG – Higher Order Discontinuous Galerkin for the Exa Scale [5] at the HPC group at University of Augsburg. The geometry model is based on latest hexahedral meshing algorithms for tubular structures [6], developed at Institute for Structural Analysis, TU Graz, and on segmentations+geometrical center line extractions (from real patient CT-data!) [7] developed at Institute of

Computer Graphics & Computer Vision. This framework is then used to generate a set of simulation data based from input samples of random field realizations computed by the Institute of Theoretical Physics, TU Graz (S. Ranftl) similar as in [1]. Altogether, this is then the dataset to machine-learn the physics from in order to get fast approximate estimates for the simulations, which are still too costly to sample from extensively. This machine-learning task is exactly the scope of this Master's project (the data will be provided), and will be supported by Computer Science faculty. The machine-learned approximator or surrogate is lastly used to compute marginal probability distributions of mechanical observables. This constellation of know-how and technology is absolutely unique world-wide, and allows for the first time the demonstration of a completely new frontier of Uncertainty Quantification in Fluid-Structure-Interaction, enabled through the joint effort and state-of-the-art in machine learning, probability theory, fluid-structure interaction, exa-scale computing, meshing and biomechanics.



1 Figure 1. Left: Illustration of one particular random field realization on the manifold representing the arterial wall of the iliac bifurcation, the geometry is reconstructed from real patient CT-data. (x,y,z) are coordinates in space, the color bar indicates values for the material property of elastic embedding. This defines an input field to a non-linear partial differential equation system (Navier-Stokes coupled with solid balance equations), the solution of which yields the spatial Cauchy stress distribution in the tissue, flow fields etc (Right). These results can then be used by surgeons to understand where locally tissue is overly strained, stressed or damaged. A statistical uncertainty evaluation is necessary due to stochastic nature of some parameters, which is impossible directly, but feasible approximately through machine-learning surrogates.

Your profile:

- Specific experience or interest in machine learning, Bayesian probability theory or statistics
- Coding experience required
- General interest in interdisciplinary applications, especially computer simulations / scientific computing / computational physics and/or human medicine and/or biology
- Courage to set foot on uncharted terrain, explore a new frontier
- Ready to take on a real challenge
- You enjoy working in a highly interdisciplinary, multi-cultural team *and* independently

What you can expect:

- Be integral part of cutting edge research project
- Learn state-of-the-art machine learning skills
- Dip into mechanical and biomedical engineering, explore further career opportunities
- Publish in the *best* journals of the field

- Full inclusion in our interdisciplinary, international team with researchers from: Physics, Computer Science, Mechanical+Civil+Electrical Engineering & Maths, Cardiovascular Surgery, with currently 4-5 experts in machine learning for engineering/physics problems you can learn from.
- Extensive mentoring on a day-to-day basis at eye level, preparing you for a career in academia *and* industry (incl. but not limited to physics, machine learning, mechanical or biomedical engineering)
- Compensation: ~ 2500 - 3000 € gross total

Lingua Franca: English

Start date and duration: flexible

Need more information? Feel free to contact Sascha Ranftl (ranftl@tugraz.at). Check out the Team's Homepage: biomechaorta.tugraz.at. Please send applications and/or inquiries for further information using the subject header [Application Deep Iliac - YOUR FAMILY NAME] to Dr. Sascha Ranftl (ranftl@tugraz.at). Applications will be reviewed for interviews on a rolling basis starting from 15th October 2023.

References:

- [1] Ranftl, S., Rolf-Pissarczyk, M., Wolkerstorfer, G., Pepe, A., Egger, J., von der Linden, W., & Holzapfel, G. A. (2022). Stochastic modeling of inhomogeneities in the aortic wall and uncertainty quantification using a Bayesian encoder–decoder surrogate. *Computer Methods in Applied Mechanics and Engineering*, 401, 115594.
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- [3] Schussnig, R., Rolf-Pissarczyk, M., Holzapfel, G. A., & Fries, T. P. (2021). Fluid-Structure Interaction Simulations of Aortic Dissection. *PAMM*, 20(1), e202000125.
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- [6] Bošnjak, D., Pepe, A., Schussnig, R., Schmalstieg, D., & Fries, T. P. (2023). Higher-order block-structured hex meshing of tubular structures. *Engineering with Computers*, 1-21.
- [7] Scharinger, B., Pepe, A., Jin, Y., Gsaxner, C., Li, J., & Egger, J. (2023, April). Multicenter aortic vessel tree extraction using deep learning. In *Medical Imaging 2023: Biomedical Applications in Molecular, Structural, and Functional Imaging* (Vol. 12468, pp. 341-347). SPIE.

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