Projet de Recherche Doctoral – SCAI AAP 2025

DeepAneurysm

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Keywords – Abdominal aortic aneurysm; rupture; FSI; pulsatile blood flow; model-order reduction; AI

Context – An abdominal aortic aneurysm (AAA) consists of a dilatation of the lower part of the aorta, before the bifurcation to the iliac arteries that irrigate the legs. The issue for clinicians remains to determine the risk of rupture and the necessity to intervene surgically (the clinical act being typically through mini-invasive routes nowadays) during the follow-up of the patients. Hemodynamic numerical simulations are promising, as they would provide clinicians with biomechanical patient data, which would be help them make decisions. Indeed, current decisions are typically made based solely on pure geometrical parameters of the AAA. But solving the equations governing the blood flow within the aneurismal abdominal aorta is challenging. To enumerate a few of the challenges, one has to solve a stiff fluid-structure interaction (FSI) problem, with non-linear material and fluid properties, and complex boundary conditions (e.g. strongly pulsatile pressure-driven flow conditions; anchorage at the levels of the diaphragm, pelvis and vertebral column; need to model at least the compliance and resistance of the downstream vessels), see [1].

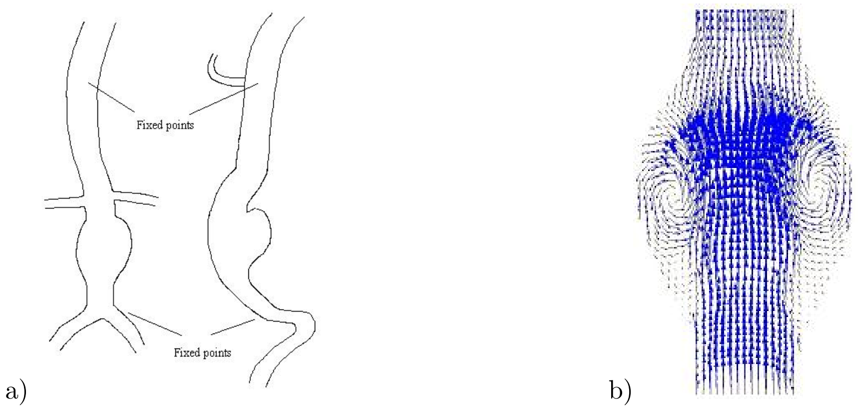

Figure 1: a) Sketch of an abdominal aortic aneurysm [2]; b) Blood velocity field in a fusiform aneurysm, measured by PIV [3].

The integration of Machine Learning (ML) and Physics has fostered a mutually beneficial relationship, leading to the development of both Physics-informed and Physics-inspired models, in particular for cardiovascular Biomechanics [4]. An important application area for these advanced models is Reduced Order Modeling (ROM). ROM aims at providing computationally efficient alternatives to large, data-intensive models, particularly important for real-time simulation and control in critical systems [7], but most approaches struggle to predict and generalize well to nonlinear and complex high-dimensional dynamical systems such as those of interest in this project.

Koopman theory provides a robust mathematical framework for dealing with complex dynamical systems by assuming the existence of an infinite dimensional space in which the dynamics are linear. This concept has been applied in various ML implementations [8], but it involves expanding the number of dimensions (observables) towards infinity, which is often impractical and different from the ROM framework that our work seeks to integrate. Recent research has attempted to combine ROMs with Koopman theory by providing closure models for unrepresented observables [9, 10]. However, these closure models often rely on delay embedding and parabolistic predictions. With recent advances in generative AI architectures, both aspects of such closures could potentially be represented by relying on ML strategies.

Scientific objectives, originality – The idea behind our project is to modernize and leverage numerical AAA simulations with Artificial Intelligence (AI) to make their use easier in the medical community and the procurement of the biomechanical patient-specific data possible within less than one minute, which is a real challenge. On the fundamental science side, and as mentioned above, our objective is to investigate state-of-the-art data-driven identification algorithms for high-dimensional spatio-temporal problems from previous high-fidelity simulations, possibly readjusted with patient data/measurements. We hope they will enable live visualizations of quantities and fields of interest (stress fields, risk assessment according to the evolution) for decision-making (surgical decision, surgical procedure).

Justification of the scientific approach – Current computational Physics-based solvers can provide accurate results but are very time-consuming. For medical use, a breakthrough is needed to lower the computational time by at least 3 or 4 orders of magnitude. We believe that a smart synergy between Full-Order models (FOM) and AI-based strategies can take up this challenge.

Alignment with the SCAI Institute and PostGenAI@Paris – This exploratory project adopts an interdisciplinary approach including Biomechanics, scientific Computing, advanced AI/ML methods, data Science and medical applications.

Role of each supervisor

– F. De Vuyst (UTC, principal supervisor) is Prof. PU1 CNU 26, affiliated with the Biomechanics and Bioengineering lab. His areas of expertise include numerical analysis, computational methods for PDEs, and general approximation methods. Part of his research focuses on MOR techniques and potential synergies between ROM methods and ML for fluid mechanics and fluid-structure interaction problems. He is responsible for the MSc Degree program "Complex System Eng." at UTC where he teaches SML. For the project, he will contribute his knowledge and skills in ROM (e.g. geometry reparametrization, see [11]) and SML (AE, possibly GNN for mesh and field interpolation).

– I. Mortazavi (CNAM, co-supervisor) is Prof. PUEX1 CNU 26, affiliated with the M2N lab (former Director), expert in computational methods for Fluid Mechanics, especially for Navier-Stokes equations and turbulence modeling. He is also strongly involved in dimensionality reduction techniques and ROMs (POD, Spectral POD, (E)DMD, Koopman theory, quadratic manifold learning, ...).

– A.-V. Salsac (UTC, co-supervisor) is DR2 CNRS in Section 10, specialized in biofluids applied to the study of hemodynamics from the large blood vessels to the microcirculation, and of endovascular treatments. She received various prestigious prizes and projects (e.g. Medal of the National Order of Merit in 2016, ERC Consolidator grand in 2018, co-PI of a CAP of PostgenAI@Paris in 2024). Her research combines highly fundamental studies with applied aspects (strong collaborations with clinicians and industries such as ANSYS, Guerbet, ...

We believe that this doctoral project is a great opportunity for the two ASU labs to collaborate together, sharing their experience and different expertises on this challenging problem.

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