CT-2-CFD: CT-based hemodynamics estimation with deep learning methods

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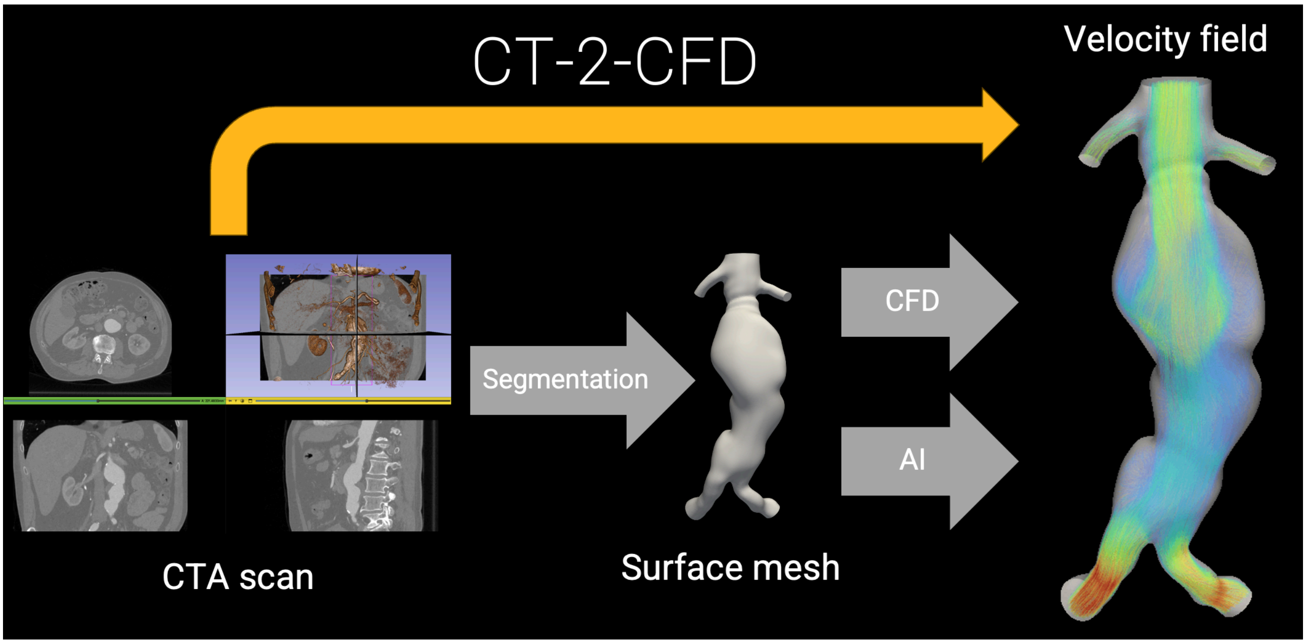
The study of blood flow dynamics (hemodynamics) is essential in assessing cardiovascular disease severity and progression. The usual way of *in-silico* modelling of hemodynamics is to employ Computational Fluid Dynamics (CFD), a numerical approach to solving the Navier-Stokes equations that govern fluid dynamics. However accurate, CFD simulations are known to be very computationally demanding in terms of both time and resources required. To remedy that, in recent years, geometric deep learning methods operating directly on 3D shapes have been proposed as compelling surrogates of CFD by providing accurate estimates in just a few seconds [1,2]. Nevertheless, they still require the prior segmentation step of the vasculature of interest and its proper meshing, which usually requires intermediate human supervision.

This project aims to explore the possibilities of hemodynamics estimation directly from the imaging, skipping the segmentation step and allowing faster and more automatic CFD surrogates to be developed. The project will focus on hemodynamic factors prediction in patients suffering from abdominal aortic aneurysms (AAAs), which are pathologic dilations of the abdominal aorta. In this project, you will explore various state-of-the-art deep learning methods allowing for data-efficient and accurate training of CFD surrogates: group-equivariant neural networks [3], physics-informed neural networks (PINNs) [4] etc.



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[3] Cohen, T. S., & Welling, M. (2016). Group Equivariant Convolutional Networks. https://arxiv.org/abs/1602.07576

[4] Thuerey, N., Holl, P., Mueller, M., Schnell, P., Trost, F., & Um, K. (2021). Physics-based Deep Learning. WWW. https://physicsbaseddeeplearning.org