MACHINE LEARNING AND REDUCED ORDER MODELLING FOR THE SIMULATION OF BRAIDED STENT DEPLOYMENT

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Introduction

Flow diverters are self-expanding braided stents used in the endovascular treatment of intracranial aneurysms (IAs). Nowadays, surgeons choose the most suitable device based only on their clinical experience and measurements taken on volumetric images acquired just before surgery. However, the configuration assumed by these devices once deployed within the parent vessel is not easily predictable. Given the tight timescale, there is a compelling need to develop computational models capable of simulating in real-time the deployment of flow diverters within patient-specific vessels to assist practitioners in the planning and interventional stages. Due to the large amount of degrees of freedom and the necessity to solve the contact with the wall, the computational time required by traditional techniques alone, such as finite element (FE) modelling, is excessively high. In this study, we propose a machine learning-based reduced order modelling (ROM) scheme for the prediction of the stent deployed configuration. The workflow is validated on an idealized IA model where geometrical and surgical parameters are considered.

Methods

High-fidelity simulations: The braided stent is modelled as a tubular net of interlaced wires, discretized using beam elements. Deployment simulations are performed using an efficient in-house, open-source FE solver [1]. The braided stent is first crimped by imposing a radial displacement to all its nodes, then bent along the artery centerline and finally released within the artery model, whose wall is assumed rigid [2,3]. We are interested in the final deployed configuration, hence quasi-static simulations are performed.

Idealized parametric model. The artery model is built as a tube with constant diameter D_v around the vessel centerline, which is defined using a planar quadratic Bézier curve:

$$B(t) = (1-t)^2\boldsymbol{P}_0 + 2t(1-t)\boldsymbol{P}_1 + t^2\boldsymbol{P}_2 \qquad (1)$$

where $\boldsymbol{P}_0$ and $\boldsymbol{P}_2$ are fixed and the 2D coordinates of the middle point $\boldsymbol{P}_1$ are included in the parametrization. A spherical idealized aneurysm with center $\boldsymbol{C}_a$ and diameter D_a is then added to the artery model.

High-fidelity database. For the database, we considered as parameters $\boldsymbol{\mu} = [D_v, y_{\boldsymbol{P}_1}, z_{\boldsymbol{P}_1}, D_a, y_{\boldsymbol{C}_a}, \eta]$, where $\eta \in \{0,1\}$ is the stent deployment site along the vessel centerline. A Latin hypercube sampling method is used to generate 150 combinations of $\boldsymbol{\mu}$ and the corresponding stent deployment simulations are performed. We excluded 25 cases from the training database to test the model performance once trained.

ROM. As in [4], a non-intrusive reduced basis (RB) method is used: the RBs are extracted from the training database with the proper orthogonal decomposition and Gaussian process regression is used to predict the solution expressed in the RBs space for new parameters values. The reduced order model is validated by computing the nodal and average prediction error (E_p) between FE and approximated solutions among the testing cases. The imaging technique with the best spatial resolution, 3D rotational angiography (3DRA), is considered as evaluation criterion for the prediction.

Results

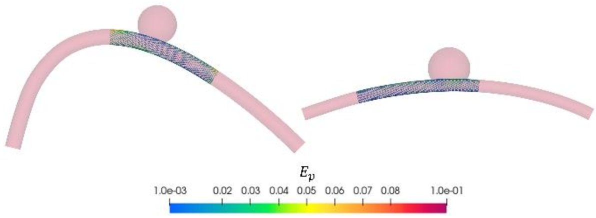

Figure 1: Predicted solutions for two testing cases with corresponding nodal E_p scale.

The average E_p decreases as more RBs are considered and reaches a stable plateau equal to 0.02 mm with 15 RBs. This is 7 times lower than the spatial resolution of 3DRA (0.15 mm). As can be seen in Figure 1, the stent configuration adapts very well to the vessel curvature.

Discussion

With the proposed workflow, results are obtained in a few ms once the ROM is trained, compared to ~1h using traditional high-fidelity techniques, while retaining the mechanical realism and predictability of the deployed configuration. The limitations of this work are the use of a parametric model that only partially reproduces the complexity of IAs and the assumption of rigid arteries. Our current efforts focus on understanding the number of parameters needed to describe patient-specific geometries and introducing deformable-wall models.

References

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