Oral presentation | Reduced order models

Reduced order models-II

Mon. Jul 15, 2024 2:00 PM - 4:00 PM Room C

[2-C-04] Simulation-Based Blood Flow Analysis using a Machine-Learning Vascular Model .

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Keywords: Blood flows, Vascular model, Machine-learning

Simulation-Based Blood Flow Analysis using a Machine-Learning Vascular Model.

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1 Introduction

Optical Coherence Tomography (OCT) is used for the assessment of coronary artery diseases and is known for its higher accuracy compared to MRI, CT, and IVUS. There is a growing effort to utilize OCT imaging to create 3D vascular models and analyze hemodynamic simulation results for the diagnosis and treatment of vascular diseases. Previous methods for reconstructing vascular models from OCT images, as shown in Figure. 1, have limitations as they generate a vascular geometry without reflecting curvature. X-ray imaging can provide a 2D view of vascular morphology and can also visualize the path of catheter insertion. To incorporate the actual curvature of blood vessels, we aim to produce patient-specific vascular geometry based on X-ray images, taking into account the curvature for more accurate blood simulations.

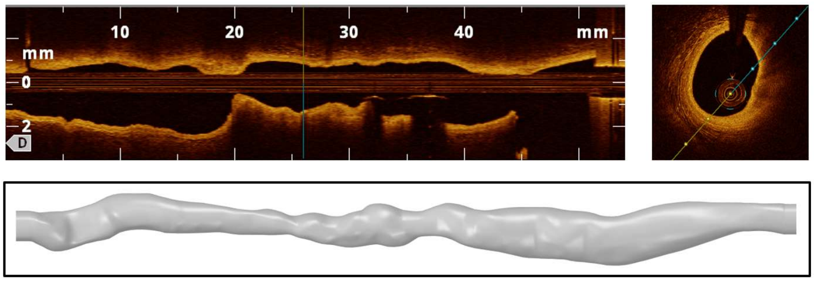

Figure 1: OCT images and vascular modeling.

2 Methods

Figure 2 illustrates the process of segmenting the lumen from OCT images. The acquired OCT images were divided into frames and converted into individual images. The original OCT images were used as input data, while a threshold parameter distinguishing between the intraluminal area and vessel wall area served as the output data for machine learning for vessel extraction. This data-set was then used to train a machine learning by using ResNet50 model. Based on the derived parameters, a binarization process was applied to extract the vascular region. From X-ray images, we extracted the intravascular path of the OCT catheter and created a 3D model by stacking segmented OCT images perpendicular to the catheter path. We employed a technique that interpolated 14 slices at intervals along the catheter path and the segmented lumen. Subsequently, we implemented a patient-specific 3D vascular geometry using Laplacian-based smoothing processing. We simulated flows in a patient-specific artery by using a finite volume method with finite difference discretization (Fluent v.2021R). In this study, the assumptions are a laminar flow, an incompressible Newtonian flow, a rigid vessel wall without elasticity. We computed velocity, pressure, wall shear stress by solving continuity equations and Navier-Stokes equations.

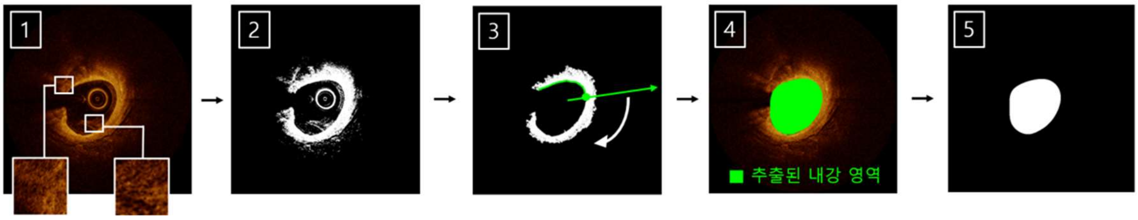

Figure 2: (1) Pixel analysis (2) Range threshold (3) Tunica intima extract (4) Segmentation (5) Lumen extraction.

3 Results

We have generated patient-specific vascular structures based on two medical imaging modalities: OCT and X-ray, commonly used for cardiovascular disease assessment. Figure 4 displays OCT images, X-ray images, and the patient-specific vascular structure (Case I) derived from these images and hemodynamic results (velocity, streamline, wall shear stress).

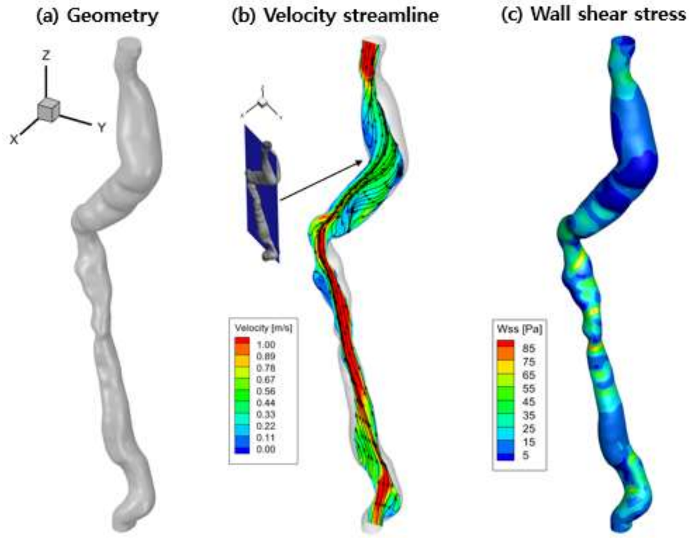

Figure 3: Patient-specific vascular model and hemodynamic results

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