Automatically hemodynamic analysis of AAA from CT images based on deep learning and CFD approaches

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Abstract. Abdominal aortic aneurysm is a serious disease which course is accompanied by the development of health complications and often leads to patient death due to aortic rupture. One of the powerful methods to estimate the risk of rupture is three-dimensional patient-specific hemodynamic analysis. In this study, we develop a software tool based on deep learning and CFD methods to perform automated computational hemodynamics with patient-specific geometry reconstructed from computed tomography images.

1. Introduction

One of the most frequent atherosclerotic lesions of the aorta is aneurismal transformations in the human abdominal region [1]. Aortic abdominal aneurysm (AAA) is a serious disease, which course is accompanied by the development of health complications and often leads to patient death due to aortic rupture [2]. The recommended method to reduce the risks of patient death and postoperative complications is early disease screening and subsequent monitoring of its progression for planning early surgical treatment. Currently, a common non-invasive method of disease screening is the analysis of computed tomography (CT) images of the abdominal part of the patient. The commonly used criterion by clinicians to schedule AAA treatment is to expand the aortic diameter greater than the norm. However this criterion has some significant drawbacks [3]. AAA rupture represents a biomechanical phenomenon, thus an appropriate tool to explore its biomechanical nature is the computational fluid dynamics (CFD). Recently, CFD simulations have been widely applied in cardiovascular research to analyze blood flow, pressure variations, and wall shear stress (WSS) distributions in human arteries [4]. In AAA cases, blood flow modelling in regions prone to transformation is performed using three-dimensional hemodynamic simulations based a on patient-specific geometry [5, 6] and boundary conditions [7, 8]. A computational study [9] performed on 3D geometries of ruptured AAA proved that rupture has occurred at sites with low WSS and recirculating flow field, probably due to endothelium degeneration. Previous contributions [10, 11] also stress the relationship between the “disturbed” flow conditions inside the lumen, for example, in regions with high and very low values of WSS or with large temporal and spatial WSS gradients, and AAA rupture risk. Thus, computational hemodynamics becomes the powerful method to predict the AAA rupture risk.

Recent studies [12, 13] show the ability of existing deep learning methods from a series of CT images to extract the geometry of the abdominal aorta appropriate to provide hemodynamic
calculations. An intermediate step before proceeding with CFD simulations is to reconstruct the 3D geometry of the aorta with a sufficient accuracy which is necessary for automatic high quality mesh processing. The importance of this procedure is shown in previous works [6], where the authors argue that wall thickness and asymmetry of the aorta have a large impact on the distribution of wall friction (WSS). Previous studies [14, 15, 16] suggest finite element methods (FEM) to provide the surface reconstruction of anatomical structures.

Despite the problem of AAA rupture risk is widely covered in the literature, there is currently no single tool for automated diagnostics of AAA based on CT images of patients that would allow one to analyze both geometric and hemodynamic characteristics of the disease. In practice, it is necessary to use software such as Mimics, VESSEG, ImFusion Suite (and other commercial packages) or open source packages SimVascular, VMTK and ITK-SNAP, etc. with further mesh smoothing algorithms [17] implemented in post-processing programs such as SolidWorks, Geomagic Studio, Autodesk MeshMixer, AngioLab (and other) or in open source packages such as MeshLab. Thus, the whole cascade of computer programs is required to prepare a patient-specific geometry for a numerical simulation. In this study, we develop a software tool for automatic hemodynamic analysis of AAA from CT images based on 3D convolutional neural networks and CFD modeling.

2. Methodology
2.1. Geometry Reconstruction

2.1.1 Computer Tomography

The CT scans used in this study were provided by the Meshalkin Institute of Circulation Pathology. The dataset consists of 20 contrast-enhanced CT images containing the abdominal aorta. CT images were obtained primarily on Toshiba Aquilion scanner series. Each slice column and rows equals 512, the pixel spacing ranges from 0.518 mm per px to 0.961 mm per px. The slice thickness is 1 mm, the axial spatial resolution is 0.8 mm per px.

![Figure 1](image)

**Figure 1.** a) original CT-images transferred to NN, b) region containing abdominal aorta, c) segmentation masks of aortic lumen (red), thrombotic masses (yellow) and calcinates (white).

2.1.2 Image Segmentation

To automatically obtain the geometry of the abdominal aorta, we use the segmentation algorithm trained by us based on neural networks, see Fig. 1. The neural network we use has U-net architecture with encoder resnext50_32x4d [18] and additional modification named squeeze and excitation blocks [19]. While U-net is originally 2D architecture, we have adapted it to work in 3D, which proved a better performance with the voxel nature of CT images.
The dataset used in this work consists of 20 CT images. Each scan contains the entire aortic abdominal region, and manual contours are delineated by clinical specialists according to a general protocol.

In order to avoid overfitting and increase data diversity, augmentations [20] such as reflection, affine and elastic transformations were used. Also, to simplify the neural network segmentation process, CT images were cropped in the region from 0 HU to 900 HU to exclude irrelevant areas.

Using leave-one-out validation method, our evaluation shows that the average segmentation accuracies by dice coefficient are 94.34%, 76.82%, 43.59% and by volumetric similarity are 97.09%, 88.51%, 52.66% for the classes of aortic lumen, thrombotic masses and calcifications, respectively.

2.1.3 3D Geometry
After AAA segmentation, Biquintic Finite Element (BQFE) interpolation technique proposed by Smith [14] were applied to reconstruct three-dimensional geometry of abdominal aortic aneurysm. Segmented masks were sent directly to input of the implemented 3D reconstruction algorithm (Python 3).

To optimize computational costs of interpolation, 3D surface coordinate data were parameterized in a cylindrical coordinate system. For this purpose, the centerline of abdominal lumen was computed as centroids of lumen masks and approximated with moving average algorithms and spline interpolation. Then the obtained central axis was subtracted from the data at each z contour.

As the error function we used the Eulerian norm without a penalty function (Sobolev norm) because the density of 3D data points is high. This algorithm allows to automatically reconstruct contiguous AAA surface of C2 continuity for hemodynamic simulations (Fig. 2a). For automatic mesh processing the geometry was divided into aortaWall, inlet, outlet patches and exported in VTK files to OpenFoam.

2.2. CFD simulations in OpenFoam
CFD simulations are a powerful tool in preoperative modeling and personal medicine. We created the AortaFoam solver in OpenFoam to automatically build mesh configuration and solve the 3D Navier-Stokes and continuity equations of fluid motion in patient-specific geometry.

![Figure 2. a) 3D reconstructed geometry b) abdominal aorta (lumen) mesh, generated with snappyHexMesh utility.](image)
Background mesh was created by using “blockMesh” tool in OpenFOAM and the 3-dimensional internal mesh containing hexahedral and split-hexahedral elements was generated from reconstructed geometry with snappyHexMesh utility (Fig. 2b). We created four layers to improve the accuracy of WSS calculations near the aorta wall.

After finite volume elements were created, boundary conditions (inlet patch, outlet patch, and aortaWall patch) and fluid rheology were determined. The results presented in [21] show that the Newtonian model is appropriate for hemodynamics analysis in aneurysms unless significant regions of high backward residence-time coexisting with low shear rates are identified. So, in this study we assumed the blood is an incompressible fluid with Newtonian properties. Blood density and dynamic viscosity are $\rho = 1040 \text{ kg m}^{-3}$ and $\mu = 0.0035 \text{ kg m}^{-1} \text{s}^{-1}$, respectively. The inner walls of the aorta are assumed to be rigid with a no-slip condition.

A model of laminar flow with constant inlet velocity profile rate was used. A uniform inlet velocity 0.05 m/s and a fixed outlet pressure was set. This velocity value is qualitatively representative of the time average of pulsatile flow [22]. The Reynolds number is $Re=220$ and is defined as $Re = \frac{2\rho u R}{\mu}$, where length scale $R = 1.5 \text{ cm}$ is the upstream aortic inlet radius and $u$ is the bulk velocity.

The semi-implicit method for pressure linked equations (SIMPLE) method was used for the computational scheme [23]. Blood velocity, pressure distributions and WSS profiles were obtained and visualized.

3. Results and discussion

Obtained results of CFD modeling were visualized with Paraview software, and velocity streamlines and WSS distribution were evaluated (Fig.3a and Fig.3b). Fig.4 presents velocity field in AAA. As can be seen from Fig. 4, there is asymmetric flow with velocity in the vicinity of AAA wall not exceeding 0.02 m/s. Despite the simplicity of the hemodynamic model we can observe the presence of vortex flows and regions with predominated low WSS that could be the reason for the increased thrombus deposition. The region of flow recirculation corresponds to the region with larger thrombotic masses of AAA.

Figure 3. a) Velocity streamlines in AAA b) WSS distribution.
Figure 4. Velocity distribution in abdominal aneurysm: a) longitudinal clip and b) surface.

In practice, any patient-specific boundary conditions could be applied in the AortaFoam Solver. For non-invasive inlet and outlet conditions assessment vector Doppler imaging and 4D Flow MRI techniques could be used. We used a laminar flow model based on the Reynolds number for average blood flow rate in cardiac cycle in reconstructed geometry, but according to previous studies [24] the turbulent flow model also could be applied especially in the regions with calcinates, intraluminal thrombotic masses and aortic bifurcations.

4. Conclusions
Three-dimensional hemodynamic modeling with patient-specific geometry allows analyzing blood flow in AAA, providing the estimation of aneurysm rupture risk based on wall shear stress (WSS) and recirculating flow field. In this study, we develop a flexible tool based on deep learning and CFD methods to perform fully automatic aortic segmentation of CT images, its 3D geometry reconstruction, and hemodynamic analysis of it. We propose that the developed tool should facilitate hemodynamic analysis and potentially could be used by clinicians.

Our further work will be aimed at ensuring the robustness of the segmentation algorithm under conditions changes in clinical data distribution due to the different parameters of CT scanners. Moreover, we plan to take into account the effect of calcinates and intraluminal thrombotic masses on blood flow in AAA and to provide simulations in turbulent flow models.

Acknowledgements. We thank N. Nikitin, I. Popova, L. Kurdyukov and E. Amelina for helping with the CT image preprocessing and D. Morozov for useful comments on the paper. The work is supported by the Russian Science Foundation grant No. 21-15-00091.

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