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RECONSTRUCTION OF THE AORTA GEOMETRY USING CANAL SURFACES

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SUMMARY

Analysis of mechanical behavior in blood flow is a relevant topic for many diseases. Wall Shear Stress (WSS) in aorta has been related to aneurysm formation. The study of this topic using simulation opens many possibilities, including the use of machine learning techniques to associate WSS profiles to different aorta geometries. In this study, we present a method to characterize the aorta geometry based on a reduced number of characteristics. Unlike approaches that rely on direct Principal Component Analysis (PCA) analysis, the method is based on geometric information that can be given anatomical meaning. We show that this method is able to characterize an aorta from Medical Image (MI) data and synthesize a new geometry with only small visible differences. We compare the WSS profiles of a real aorta and the corresponding reconstructed geometry.

Key words: *blood flow in aorta, computational fluid dynamics, computational geometry, geometry reconstruction*

1 INTRODUCTION

Simulation studies can help establish the influence of blood flow and aorta geometry on the development of different diseases [2, 7, 9]. In order to conduct studies that can relate geometry to flow properties a large number of samples is desirable. A possible solution is the generation of large sets of synthetic aortas, that are anatomically meaningful but show geometric variation [7]. In this work we present a method to characterize the main geometric features of the aortic arch and the abdominal aorta with a reduced number of features. Our method relies on geometrical features, compared to classic data analysis methods such as PCA or Neural Networks applied to the geometry [7]. Compared to other similar approaches, such as [1], the main difference is that we decouple centerline and surface extraction, leading to a more modular approach.

2 MATERIAL AND METHODS

The goal of our method is to build an analytical description of the aorta geometry that requires a reduced number of parameters. The method takes a triangle mesh that represents the aorta wall reconstructed from MI and computes the parametrization of a differentiable surface that approximates its geometry. Using this parametrization, we are able to generate a new triangle mesh with a similar geometry.

The algorithm proposed is based on the assumption that the aorta can be modelled, to some extent, as a tubular surface [5]. Without going into technical details, a tubular surface can be considered as the Cartesian product of a regular curve (which we will call *centerline*) and a regular closed curve.

In particular, Canal Surfaces use circumferences as the closed curve that generates the surface when travelling along the centerline [5]. As a result, canal surfaces can be easily parametrized using their centerline and cross sections, which are circumferences:

$$\mathbf{x}(s,\theta) = \alpha(s) + r(s)\left(-\mathbf{t}(s)r'(s) + \sqrt{1-r'(t)^2}(-\mathbf{n}(s)\cos(\theta) + \mathbf{b}(s)\sin(\theta))\right), \quad (1)$$

where $\alpha(t)$ is the centerline, $\{\mathbf{t}(s), \mathbf{n}(s), \mathbf{b}(s)\}$ is its the Frenet frame and $r(t)$ is the radius of the sections. Our algorithm will generate a similar parametrization using an evolving frame along the curve and ellipses that fit the surface that was given as input.

2.1 Algorithm

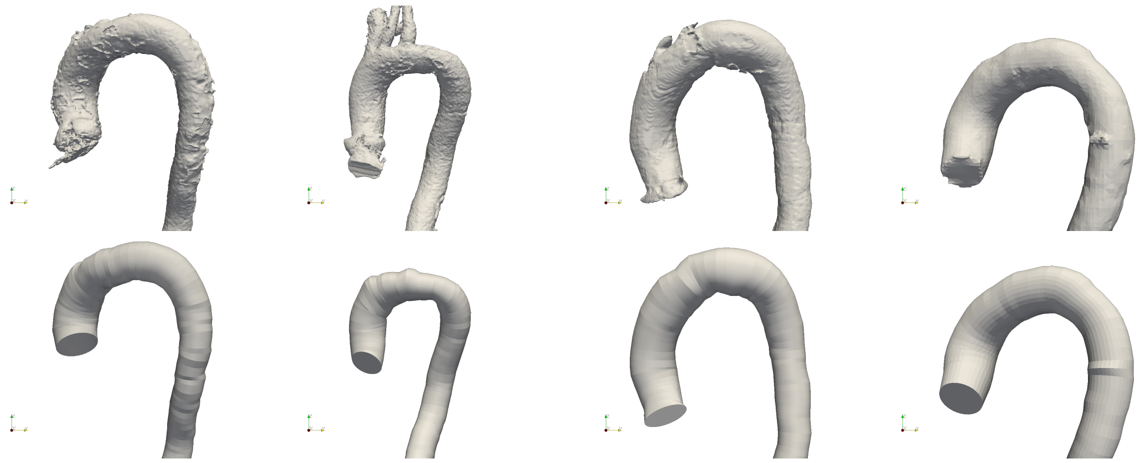
The algorithm considers as its input a triangle mesh that represents the surface of the aorta. Let V be the set of points that form the mesh. The proposed algorithm starts by computing a vector that forms an angle close to 90º with the coronal plane. In order to do this, we build a reference frame based on a PCA analysis on V. From that frame, we take $\mathbf{e}_3$ as the eigenvector associated to the resulting smallest eigenvalue. In a second step, we extract the centerline of the mesh as a set of points and approximate it as a spline, $\alpha(t)$. Then, beginning at the aortic valve, the algorithm samples $\alpha(t)$ regularly at a series of points $\mathbf{x}^i$ and computes a reference frame associated to each point, $\langle \mathbf{v}_1^i, \mathbf{v}_2^i, \mathbf{v}_3^i \rangle$. This reference frame includes the tangent to the centerline, $\mathbf{v}_1 = \mathbf{t}$, a vector $\mathbf{v}_2$, orthogonal to both $\mathbf{v}_1$ and $\mathbf{e}_3$, and $\mathbf{v}_3 = \mathbf{v}_1 \times \mathbf{v}_2$. We have two possible choices for $\mathbf{v}_2$. In the first sample point, the vector $\mathbf{v}_2^1$ is taken so that it points in the direction of the descending aorta. From then on, each new vector is taken so that it does not twist the reference frame respect to the previous one, by ensuring $\mathbf{v}_2^{i-1} \cdot \mathbf{v}_2^i > 0$. For each reference frame we compute the intersection between the original mesh and the plane defined by $\mathbf{v}_2$ and $\mathbf{v}_3$, and adjust an ellipse to that set of points by least squares fitting [6]. The information of the ellipse is stored alongside the reference frame and defines the reconstructed section of the aorta at that point of the centerline.

When the process finishes, the aorta has been represented by means of the locations of the points on the centerline, and the associated reference frames and elliptical sections. From this information it is possible to reconstruct a mesh by sampling the elliptical sections using an expression equivalent to (1). If a mesh is required with a resolution higher than that provided by the generated sections, then some interpolant surfaces, such as NURBS [4], can be used.

3 RESULTS AND DISCUSSION

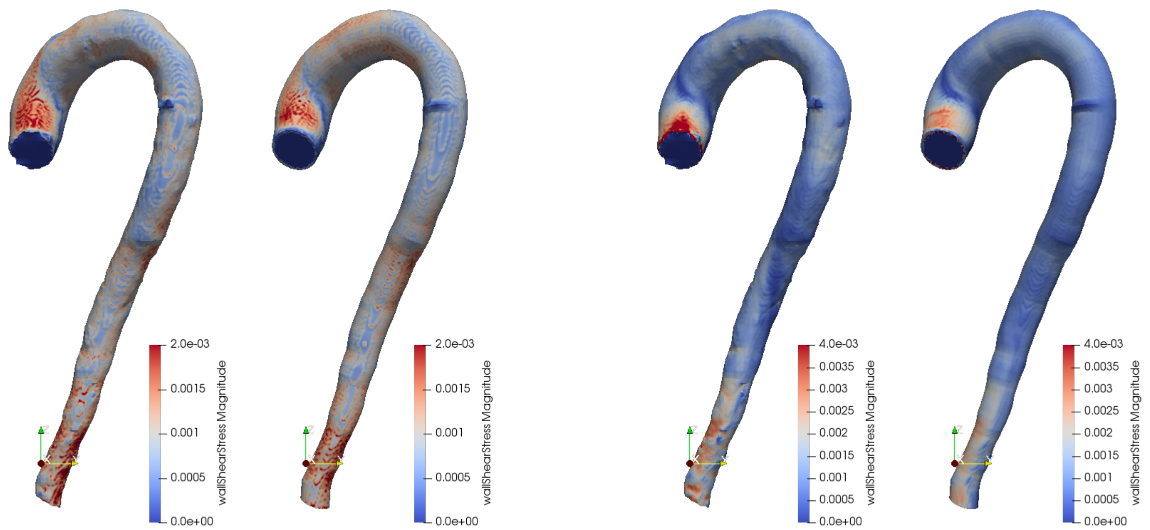
So far, the method has been tested with 8 aortas acquired from Computerized Tomography (CT) in a retrospective sampling. The different samples were of patients with over 60 years old and different pathologies, and where acquired in the mesosystole phase of the cardiac cycle. Figure 1 shows four aorta geometries with the corresponding reconstructions. The algorithm has been applied to the geometries without an smoothing step except in one case. The method has been able to reproduce the geometry of the aortic arch and the descending aorta with only small visible differences when using over 75 cross sections on the centerline. However, since it tries to fit each section using a single ellipse, the region of the sinuses of Valsalva is not properly reproduced. An specific treatment of this region will be required in future research. Nevertheless, the method has proved to be very robust in what regards noise and the inclusion of the different aorta branches in the original mesh as it can be seen in Figure 1, (a) and (b).

Since our final goal is to be able to generate aorta geometries in order to perform Computational Fluid Dynamics (CFD) simulations, we have run a simulation of blood flow in an aorta acquired from CT and the reconstructed geometry using our method. According to [3], blood can be considered as an incompressible Newtonian fluid in large arteries such as the aorta. We set a kinematic viscosity of value $\nu = 3.37 \cdot 10^{-6}$ m^{2}s, following [2]. We solve Navier-Stokes equations by means of the CFD software OpenFOAM [8], based on the Finite Volume Method. Boundary conditions applied try to reproduce peak systolic conditions which are the following: for velocity, a uniform profile of 0.68 m/s on the inlet, a non slip condition on the aorta wall and a zero gradient condition on the outlet;



(a) (b) (c) (d)

Figure 1: Four examples of aortas acquired from CT (above) and the corresponding reconstruction using the method proposed (below). In case (b) it can be seen how the method is able to reconstruct the aorta lumen even though aortic branches are present. Case (d) was the only one smoothed before the reconstruction, and is the aorta used for CFD simulation.



(a) (b) (c) (d)

Figure 2: Wall Shear Stress (m^2/s^2) distribution on the aorta wall after 0.5s of simulation. Flow without turbulence model on the real aorta (a) and on the reconstructed geometry (b). Flow with $k-\epsilon$ turbulence model on the real aorta (a) and on the reconstructed geometry (b). Note that the color scale is not the same in both cases.

for pressure we applied a zero gradient condition on every patch except for the outlet where we set a zero value boundary condition. A spatial resolution of 1.5 and 0.75 mm is used near the center and the wall, respectively. With this resolution, the number of cells has been 173340 for the real aorta mesh and 171303 for the reconstructed aorta mesh. Time resolution has been of 1 ms. The simulation has been let evolve until the flow becomes stable. The results are shown for the state of the simulation after 0.5s. We measure wall shear stress (WSS) on the aorta wall, defined as the tangential component of the traction force $\tau(\mathbf{n})$ on the surface, where τ is the stress tensor and $\mathbf{n}$ the vector normal to the wall. It must be said that OpeanFoam provides wall shear stress divided by the density of blood, set as $\rho = 1040$ kg/m^3.

Since the maximum Reynolds number has been estimated to be around 10000 we have run an additional simulation using the $k-\epsilon$ model for turbulent flow. As a result, we have four simulations: two simulations for the original mesh and two simulations for the reconstructed mesh. Figure 2 presents the results of the simulations. Even though the results are very preliminary, the most noticeable macroscopic WSS patterns that appear on the original aorta mesh are reproduced when using the reconstructed surface. This might indicate that the proposed characterization would be able to store geometric information relevant to reproduce WSS profiles.

The proposed characterization of the geometry offers a low-dimensional representation of the aorta that can be used as a characteristic vector for statistical or machine learning analyses. By means of Statistical Shape Modelling, a large dataset of aorta geometries can be generated to run simulations and characterize different WSS profiles from the geometry. Compared to other dimensional reduction techniques, such as PCA or Neural Network approaches [7], our approach is based on geometry and, thus, characteristics are more meaningful even from a clinical point of view.

The method, however, is still at an early stage and requires further improvement. First of all, there are some free parameters, such as the number of elliptic cross sections, or the degrees of freedom of the centerline that need to be fixed to have an standard characterization. The proper selection of these and other parameters needs to be done using a larger sample of aortas to determine which are more discriminant of the intra-population variations.

The method, in its current form, does not reconstruct the sinuses of Valsalva and is not able to build the main aorta branches. Using a centerline extraction that is able to reproduce branching would enable this feature. The location and orientation of these branches should also be considered as relevant features.

REFERENCES

[1] Luis Alvarez, Agustín Trujillo, Carmelo Cuenca, Esther González, Julio Esclarín, Luis Gomez, Luis Mazorra, Miguel Alemán-Flores, Pablo G Tahoces, and José M Carreira. Tracking the aortic lumen geometry by optimizing the 3d orientation of its cross-sections. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 174–181. Springer, 2017.

[2] J. Casacuberta, E. Soudah, P.J. Gamez-Montero, G. Raush, R. Castilla, and J. Pérez. *Hemodynamics in the thoracic aorta using OpenFOAM: 4D PCMRI versus CFD*. CINME, 2015.

[3] David Elad and Shmuel Einav. Physical and flow properties of blood. *Standard handbook of biomedical engineering and design*, pages 3–1, 2003.

[4] James D. Foley, Andries van Dam, Steven K. Feiner, and John F. Hughes. *Computer Graphics: Principles and Practice (2Nd Ed.)*. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1990.

[5] Alfred Gray, Simon Salamon, and Elsa Abbena. *Modern Differential Geometry of Curves and Surfaces with Mathematica*. Chapman and Hall/CRC, 2006.

[6] Radim Halir and Jan Flusser. Numerically stable direct least squares fitting of ellipses, 1998.

[7] Liang Liang, Minliang Liu, Caitlin Martin, and Wei Sun. A deep learning approach to estimate stress distribution: a fast and accurate surrogate of finite-element analysis. *Journal of The Royal Society Interface*, 15(138):20170844, 2018.

[8] OpenFOAM Foundation. OpenFOAM. `http://www.openfoam.org`. Accessed: 2019-02-28.

[9] Rodrigo M. Romarowski, Adrien Lefieux, Simone Morganti, Alessandro Veneziani, and Ferdinando Auricchio. Patient-specific cfd modelling in the thoracic aorta with pc-mri–based boundary conditions: A least-square three-element windkessel approach. *International Journal for Numerical Methods in Biomedical Engineering*, 34(11), 11 2018.