In silico modeling for personalized stenting in aortic coarctation

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\section*{ABSTRACT}
Stent intervention is a recommended therapy to reduce the pressure gradient and restore blood flow for patients with coarctation of the aorta (CoA). A remaining challenge for physician is to select the optimal stent before treatment. Here, we propose a framework for personalized stent intervention in CoA using in silico modeling, combining image-based prediction of the aortic geometry after stent intervention with prediction of the hemodynamics using computational fluid dynamics (CFD). Firstly, the blood flow in the aorta, whose geometry was reconstructed from magnetic resonance imaging (MRI) data, was numerically modeled using the lattice Boltzmann method (LBM). Both large eddy simulation (LES) and direct numerical simulation (DNS) were considered to adequately resolve the turbulent hemodynamics, with boundary conditions extracted from phase-contrast flow MRI. By comparing the results from CFD and 4D-Flow MRI in 3D-printed flow phantoms, we concluded that the LBM-based LES is capable of obtaining accurate aortic flow with acceptable computational cost. In silico stent implantation for a patient with CoA was then performed by predicting the deformed geometry after stent intervention and predicting the blood flow. By evaluating the pressure drop and maximum wall shear stress, an optimal stent is selected.

\section*{1. Introduction}
Coarctation of the aorta (CoA) refers to a local narrowing of the aortic arch. It makes up 6–8\% of all congenital heart diseases (Rafieianzab et al., 2021), and is often associated with other cardiovascular diseases, such as aortic arch hypoplasia, subaortic stenosis, ventricular and atrial septal defects (Alkashkari et al., 2019; Hoffman & Kaplan, 2002; Reller et al., 2008). The coarctation leads to high blood pressure and thus heart damage. Stent intervention, which is generally performed based on clinical experience without theoretical guidance, is a recommended therapy to reduce the pressure gradient and restore blood flow.

With increasing computational power, in silico modeling is emerging as a promising tool to help clinicians with intervention planning and to evaluate the outcome of therapies, such as stenting for intracranial aneurysm (Berg et al., 2018; Zhong et al., 2016), abdominal aortic aneurysm (Pionteck et al., 2021), and type-B aortic dissection (D. Chen et al., 2018; Kan et al., 2021). By taking personalized information as input, modeling also supports the design of patient-specific medical implants (McCloy & Stone, 2001).

For in silico modeling of personalized stent intervention in CoA, a protocol for virtual geometry deformation (Neugebauer et al., 2016) and a validated numerical method to accurately predict the blood flow in the aorta are required. Regardless of the erythrocytes, leukocytes, and platelets in blood, the flow in the aorta is normally modelled as Newtonian fluid (Pedley, 1980) considering the relatively large Reynolds number \( Re \), which is proportional to the flow velocity and aorta diameter and inversely proportional to the blood viscosity. Computational fluid dynamics (CFD) (Taha, 2005) plays an important role in biomedical engineering applications, such as drug delivery (Alishiri et al., 2021) and understanding of carotid stenosis (Kang, Mukherjee, Kim et al., 2021; Kang, Mukherjee, & Ryu, 2021) and aortic dissection.
(Cheng et al., 2013, 2015). Due to the personalized and complex 3D geometry and jet flows induced by heart contraction and local narrowing, laminar flow, turbulent flow and transition between them may coexist spatiotemporally (Ku, 1997; Stein & Sabbah, 1976). Thus, to accurately resolve such aortic flow, both turbulence and complex geometry should be considered in CFD simulations. Three approaches, including Reynolds-averaged Navier–Stokes equations (RANS), large eddy simulation (LES), and direct numerical simulation (DNS), are typically used for turbulence modeling. From RANS to DNS, both the accuracy and computational demand increase due to more and more details that need to be resolved.

So far, mainly RANS and LES were used to study aortic flow in literature (Caballero & Laín, 2013). With a transitional model, RANS was adopted to resolve flows in patient-specific thoracic aortic aneurysm by Tan et al. (2009) and aortic dissection by Cheng et al. (2013, 2015). Simulations were carried out using ANSYS CFx, a commercial finite volume-based solver. Kouseral et al. studied flow stability in a normal aorta using the same numerical method and compared their numerical results with experimental data from in vivo magnetic resonance imaging (MRI) (Kousera et al., 2012). They concluded that the RANS-based shear stress transport transitional model was capable of capturing the correct flow state when low inflow turbulence intensity (1.0%) was specified. Miyazaki et al. validated three CFD models for aortic flows in the aorta of a healthy adult and a child with double aortic arch (Miyazaki et al., 2017). Laminar, LES and the renormalization group (RNG) k-ε model were considered and compared. Simulations were performed using another finite volume-based solver, ANSYS Fluent. Their results show that the RNG k-ε model has the highest correlation with data from 4D flow MRI. Recently, Manchester et al. used LES to study the blood flow in patient-specific aorta with aortic valve stenosis (Manchester et al., 2021). Here, the finite volume-based open-source library OpenFOAM was used. After investigating the fluctuating kinetic energy, wall shear stress (WSS) and energy loss, they concluded that turbulence played an important role in aortic hydrodynamics.

It should be noted that severe turbulence will be encountered in CoA due to more complex geometry and larger Re, which might lead to higher requirements on the CFD method. The aforementioned conventional CFD methods are based on discretizations of macroscopic governing equations, such as the Navier-Stokes (NS) equations. Alternatively, the lattice Boltzmann method (LBM) is based on the mesoscopic Boltzmann equation and has multiple advantages, including simple handling of complex geometric shapes, ease of programming, and suitability for parallelization (S. Chen & Doolen, 1998; Y. He et al., 2009; Krüger et al., 2017). Therefore, the LBM is increasingly used for the simulation of turbulent flow (H. Chen et al., 2003) and biological fluid flows (Wang & Elghobashi, 2014). Hennt et al. simulated the unsteady blood flow in a patient-specific geometry with a moderate thoracic aortic coarctation and demonstrated that the LBM-based DNS was capable of resolving such complex flow (Henn et al., 2013). Recently, Mirzaee et al. studied aortic flows for 12 patients with CoA using the LBM-based LES, particularly with the Smagorinsky turbulence model (Mirzaee et al., 2017). A reasonable agreement for pressure drop between the numerical results and the catheter measurements was achieved. Nevertheless, to guide in silico stent intervention for CoA, a comprehensive validation for the LBM-based LES for complex flow is still missing.

Since the 1970s and 1980s, MRI has become an important clinical and scientific tool that is widely used for diagnosis, monitoring of treatment procedures, and for biomedical research (Markl et al., 2012). Compared with X-ray and computed tomography, one of the advantages of MRI is the use of non-ionizing radiation (Landheer et al., 2020; McRobbie et al., 2007). In addition to obtaining anatomical information, MRI can also be used for quantitative flow measurements using phase-contrast imaging (Moran, 1982; O’Donnell, 1982; Soulat et al., 2020), including measurement of aortic blood flow (Miyazaki et al., 2017; Saitta et al., 2019).

In this study, we developed a framework for personalized stent intervention in CoA using in silico modeling, combining CFD and image-based virtual geometry deformation. Such framework can provide the optimal stent plan based on flow simulations, before clinical intervention. A comprehensive validation of the LBM-based LES for aortic flow was also performed. Geometries for a patient-specific aorta with CoA, before and after stent intervention, were considered and physical phantoms were created using 3D printing for use in MRI flow experiments. Flow measurements obtained with MRI scans were then used as boundary conditions for simulations. Obtained numerical results using LBM-based LES and DNS were then compared with experimental 4D-Flow data. To further validate the LBM-based LES, we also compared within vivo data. We demonstrated that LES is capable of accurately simulating complex aortic flow and further applied it for in silico stent implantation. Details of the methodology are given in Section 2. Numerical results and experimental measurements for aortic flows are presented and compared in Section 3. The application for stent selection is provided in Section 4. Discussion, limitations of the current work and future works can be found in Section 5. A conclusion is given in Section 6.
2. Methodology

2.1. MRI experiments

The anatomical structure of the aorta and the flows therein were acquired by MRI, which provided realistic geometries and boundary conditions for CFD simulations. Comparison between CFD and phase-contrast flow MRI for flows in 3D-printed phantoms and in vivo aorta were performed, respectively.

For the phantoms, the 3D anatomies of the heart and aorta of a 14-year-old patient with CoA, before and after stent intervention, were reconstructed from images obtained by a Magnetom Skyra 3T (Siemens Healthineers, Erlangen, Germany). The stent (diameter = 12 mm) used in this patient was a covered Cheatham-platinum (CP) stent made of platinum-iridium (NuMed, Orlando, USA). The sequence parameters are listed in Table 1. Using ITK-SNAP (Yushkevich et al., 2006), the geometry that starts from the aortic root and ends above the diaphragm was segmented based on the gray values and exported as STL file. The main branches, such as the right subclavian, the left subclavian, the right carotid artery and the left carotid artery, were included. To have an uniform surface mesh, the generated geometries were then remeshed using Autodesk Meshmixer (Schmidt & Singh, 2010). The schematic diagram of the experiment is shown in Figure 1. Two aortic models, including the pre-interventional and post-interventional geometries, were printed using the Stratasys’ high-end 3D laser printer Connex 3 using biocompatible MED610 as material. The phantoms were connected to a pump. Forced water flows therein were then measured using 4D phase-contrast Flow MRI (Dyverfeldt et al., 2015; Markl et al., 2012; Potters et al., 2014). The sequence parameters can be found in Table 1. Every case was measured three times for about 30 minutes per measurement. The averaged flow fields were then used for comparison.

For the in vivo validation, the aortic blood flow of a 3-year-old patient was obtained using a 2D flow sequence instead of a 4D flow sequence to reduce the duration of measurement. In the 2D measurement, the through-plane velocity of the flow was measured in two planes located in the ascending aorta and descending aorta, respectively. All in vivo measurements were made with the use of ECG triggering and respiratory gating. The in vivo measurement was performed using the same MRI scanner as the phantom experiments and more details can be found in Table 2. For further CFD simulation, the aortic geometry was segmented and reconstructed using the same procedure as mentioned above.

2.2. Numerical modeling

The CFD simulations in this study were performed using the LBM, which is based on the kinetic theory, particularly the Boltzmann equation, which describes the movements of fluid particles (S. Chen & Doolen, 1998; X. He & Luo, 1997; Y. He et al., 2009; Krüger et al., 2017). For simulations, the space and time are discretized into finite nodes and time steps. Starting from an initial state, the configuration of the fluid particles at each time step evolves into two sub-steps, streaming and collision. During streaming, fluid particles at a node move to the neighboring nodes along specified discrete directions as defined by the lattice. The streamed particles at a node collide with each other and change their velocity distribution functions (Benzi et al., 1992). For 3D flows, the most popular lattice is the D3Q19, which is used in this work.

Different operators, such as the single-relaxation-time BGK (Qian et al., 1992) and the multi-relaxation-time (MRT) operators (D’Humières et al., 2002), can be used to approximate the particle collision. We chose the MRT operator due to its better numerical stability. The governing equation for the LBM with MRT operator reads

\[ f_i(x + e_i \Delta t, t + \Delta t) - f_i(x, t) = \Lambda_{ij}(f^e_{ji}(x, t) - f_j(x, t)), \]

where \( f_i \) is the particle velocity distribution function along the \( i \)th direction; \( x \) and \( t \) are the spatial coordinate and time respectively; \( \Delta t \) is time step; \( e_i \) is the

| Geometry (pre) | Geometry (post) | 4D flow MRI (pre) | 4D flow MRI (post) |
|---------------|----------------|-------------------|-------------------|
| Sequence type | 3D FLASH (TWIST) | 3D T1 weighted FLASH | 3D Cartesian FLASH | 3D Cartesian FLASH |
| Acceleration  | 3 × 2 | 2 × 2 | – | – |
| Matrix size   | 352 × 246 | 448 × 252 | 384 × 504 | 416 × 364 |
| Number of slices | 80 | 88 | 144 | 144 |
| Slice thickness (mm) | 1.30 | 1.20 | 0.77 | 0.77 |
| Pixel size (mm²) | 1.02 × 1.02 | 0.89 × 0.89 | 0.77 × 0.77 | 0.77 × 0.77 |
| Repetition time (ms) | 2.75 | 3.70 | 36.40 | 70.40 |
| Echo time (ms) | 1.00 | 1.31 | 4.61 | 7.46 |
| Flip angle (°) | 20 | 25 | 7 | 7 |
| Velocity encoding (cm/s) | – | – | 50 | 40 |
The right-hand side of Equation (1) represents the collision process in momentum space. \( \Lambda_{ij} = M^{-1}S \); \( M \) is a given transformation matrix for the lattice; \( S \) is a diagonal matrix. Macroscopic parameters, such as the fluid density, pressure and velocity, are moments of \( f_i \).

The left-hand side and right-hand side of Equation (1) represents the streaming and the collision processes, respectively. The simplicity of this equation implies that the LBM is readily parallelizable as the non-local streaming is linear while the non-linear collision is local (S. Chen & Doolen, 1998; Y. He et al., 2009; Krüger et al., 2017). Thus, the LBM is increasingly used for turbulence modeling, especially DNS with high-performance modern computers. Additionally, due to its particle feature, even with a simple Cartesian grid, the LBM can resolve flow with complex geometry, such as the patient-specific aortas considered in this study.

The LBM-based DNS and LES were investigated in this study, based on the open-source library Palabos (Latt et al., 2021). DNS resolves the flow at all scales without empirical model in numerical experiments. As mentioned before, the calculation cost of DNS is very high, especially for flows with large Reynolds number (Moin & Mahesh, 1998; Wang & Elghobashi, 2014). Alternatively, LES explicitly solves large eddy current and implicitly calculates small eddies by using a sub-grid scale (SGS) model, thus balancing accuracy and computational cost. The Smagorinsky SGS model (Smagorinsky, 1963) was incorporated into the LBM in this study.

For all simulations, the inlet velocity with the Poiseuille profile was specified at the ascending aorta. The flow rates were given based on MRI measurements.
and can be found in the following sections. Outlet boundary condition with a reference pressure was applied to the descending aorta. The curved aortic wall was assumed to be no-slip and treated with an extrapolation scheme (Guo et al., 2002).

3. Validation and comparison

3.1. Phantom experiments

The two phantoms filled with water were used in the MRI experiments and compared to CFD simulations of the same geometries. The main branch blood vessels were closed to reduce their influence. Inlet and outlet of the geometries were extended artificially for the connection of the water pipe. Water is incompressible and Newtonian. Its density and kinematic viscosity are $1.0 \times 10^3$ kg/m$^3$ and $1.0 \times 10^{-6}$ m$^2$/s, respectively. The averaged velocity at the inlet is 0.1 m/s. The geometries with triangular surface meshes are shown in Figure 2. Quantitatively, areas of the inlet planes and six specified cross-sections, from ascending to descending aorta, are listed in Table 3. Locations of those sections can be found in the left panel of Figure 6.

First, a mesh independence test was performed. We considered at least four simulations with different spatial resolutions for each case, as shown in Figure 3. The averaged kinetic energy $E = \frac{1}{2} \sum_{i=1}^{N} \frac{u_i^2}{N}$ in the whole computational domain was monitored. Therein, $N$ is the number of lattices, $u_i$ is the local velocity. Density (or mass) is almost constant thus not considered in the definition of $E$. A smooth temporal development of $E$ can be found in all curves, as we gradually increased the inlet velocity from zero to the target value, for the purpose of better numerical stability. By comparing the curves after the statistical steady states and the corresponding computational costs, we chose the meshes with orange curves for further simulations. In summary, 12.30 million (DNS) and 3.45 million (LES) lattice nodes were selected for the pre-interventional geometry and 5.12 million (DNS) and 1.25 million (LES) lattice nodes for the post-interventional one.

Due to the complex geometry, e.g. multiple plane curvatures and branches, blood flow in the patient-specific aorta is unsteady and complicated. Instantaneous velocity contours on a sagittal plane and a coronal plane in the pre-interventional geometry are given in Figure 4. Due to the relatively low temporal resolution of 4D flow MRI, the following contours were extracted by looking at the difference between the first and the last frames in the time series.

![Image](image_url)

**Figure 2.** Aortic geometries with triangular surface meshes. Left: pre-interventional geometry; right: post-interventional one. Unit: m.

| Areas of the specified aortic cross-sections for geometries used in DNS. |
|-------------------------------------------------|
|                      | Inlet (m²) | No.1 (m²) | No.2 (m²) | No.3 (m²) | No.4 (m²) | No.5 (m²) | No.6 (m²) |
|--------------------|------------|------------|------------|------------|------------|------------|------------|
| Pre-interventional | 9.404e−05  | 4.175e−04  | 8.625e−05  | 1.380e−04  | 2.725e−05  | 2.544e−04  | 2.4780e−04 |
| Post-interventional| 6.859e−05  | 4.050e−04  | 8.857e−05  | 1.401e−04  | 1.281e−04  | 1.705e−04  | 1.194e−04  |
Figure 3. Mesh independence test. Time histories of the averaged kinetic energies in the aortic geometries. Top row is for the pre-interventional geometry; from left to right, DNS and LES. Bottom row is for the post-interventional geometry; from left to right, DNS and LES.

Here only results from DNS and LES are presented. It can be seen that the flow therein is turbulent. Because of the local narrowing in the stenosis, flow is accelerated in the pre-interventional geometry and the local Reynolds number on the stenosis plane is more than 2500. Jet flow, which leads to high blood pressure and high wall shear stress (WSS), is observed. DNS provides more flow details due to higher spatial resolution.

As the flow is unsteady, temporal averaging was performed for both CFD and MRI results and the following comparison is based on the time-averaged flow fields. The main flow features can be found in Figure 5. The visualization of 3D streamlines and velocity vectors on the sagittal plane (insets) shows the complexity of the flow within the patient’s aorta, especially where the stenosis occurs. Again, jet flow and recirculation are observed in the pre-interventional geometry in the streamlines and highlighted in the zoomed-in insets. Helical streamlines can also be found in all cases. For the MRI results, some streamlines start from the vessel wall as no-slip boundary condition is not guaranteed in MRI data. Nevertheless, all methods, including DNS, LES and MRI, resolved the main flow features. Moreover, as the aorta is deformed and flattened after stent implantation, the flow resistance in the post-interventional geometry is reduced. The pressure drop is reduced from 790 Pa (DNS) and 778 Pa (LES) to 9 Pa (DNS) and 8 Pa (LES), respectively. Those results indicate that stent implantation restored the aortic flow effectively.

Figure 6 presents quantitative comparison of mean velocity magnitude on six specified cross-sectional planes. These six planes, as shown in the left panel of Figure 6, represent the ascending, arch, pre-stenosis, on-stenosis, post-stenosis and descending of the aorta respectively. The mean velocity magnitude was calculated according to $\sqrt{\frac{\sum_{i=1}^{N} (U_i^2 + V_i^2 + W_i^2)}{N}}$, with $N$ the number of points on a cross-plane. It can be seen from the right panel of Figure 6 that the MRI results are a little larger than the numerical ones on planes Pre 2, Pre 3 and Pre 5. Using MRI results as a reference, the relative deviations for LES and DNS are 4–28% and 7–27%,
Figure 4. Instantaneous velocity contours on a sagittal plane and a coronal plane in the pre-interventional geometry of an aorta of a patient with CoA simulated by CFD. Left: DNS; right: LES.

Figure 5. Streamlines of the flow computed with CFD simulations of the aorta compared to MRI measurements of the flow in the 3D-printed phantoms. The time-averaged flow is shown. The insets show the velocity vectors on the sagittal planes. Top: pre-interventional geometry; bottom: post-interventional geometry.
Kinetic energy of the fluid, $K$, is calculated as $K = rac{1}{2} ho u^2$, where $\rho$ is the density of the fluid and $u$ is the velocity. The results of this calculation are tabulated in Table 2, with the following units: $\text{kg/m}^3\cdot\text{m}^2/\text{s}^2$. The table shows a range of values from 100 to 1000 $\text{kg/m}^3\cdot\text{m}^2/\text{s}^2$, indicating a high kinetic energy in this fluid flow. The data is further analyzed in Section 4.2 for more detailed insights into the flow dynamics.
**Figure 7.** Flows in pre-interventional aorta. Velocity magnitude distributions were compared among CFD simulations and 4D Flow MRI on six planes as shown in Figure 6. Time-averaged results.

**Figure 8.** Flows in post-interventional aorta. Velocity magnitude distributions were compared among CFD simulations and 4D Flow MRI on six planes as shown in Figure 6. Time-averaged results.
The geometry extends from the aortic root to the descending aorta and includes branch vessels as shown in Figure 10. Both the inlet and outlet planes were approximately circular after the geometry was remeshed and smoothed. We did not consider the deformation of the aorta, or fluid-solid interaction and assumed that the wall was not moving. A velocity profile based on the experimentally recorded flow rate was specified as inlet. Specifically, the flow rate $Q_{in}$ was calculated according to $Q_{in} = \sum_{i=1}^{N} V_i \cdot S_i$. Here $V_i$ is the pixel-velocity obtained from 2D flow MRI, $S_i$ is the area of each pixel in the inlet plane, $N$ is the total number of pixels in the inlet plane. A parabolic profile with the same amount of flow rate was then generated in Palabos as inflow boundary condition. A pressure boundary condition, with a specified reference pressure, was defined as outlet at the opening in the descending aorta, as velocity profile over there was unknown. Since the vessel branches were open in this test, the difference in flow rates between the inlet and outlet were assigned to the branches according to their cross areas (Mirzaee et al., 2017; Pirola et al., 2017).
The time-averaged flow fields are given in the right panel of Figure 10. At \( t_1 \) (the instant with peak flow rate), the through-plane component of mean velocity from LES is 0.69 m/s, with relative deviation 8% in reference to the MRI result, 0.75 m/s. Similarly, at \( t_2 \), the through-plane component of mean velocities are 0.55 m/s (LES) and 0.49 m/s (MRI). Thus, good agreement between LES and MRI was also achieved in vivo. Moreover, LES with proper boundary condition could provide more flow details due to higher spatial resolution, as shown in both in vivo and phantom tests.

4. Application for stent selection

4.1. Geometry deformation

The main motivation for silico stent implantation is to help clinicians to evaluate the surgical plans based on predicted results and to be able to select an optimal stent already before surgery. A fast virtual stenting approach proposed by Neugebauer et al. (2016) was implemented in this work to generate virtually deformed geometries. Several parameters, such as the aorta bending resistance, aorta stiffness, stent stiffness, stent position and diameter were considered in this approach to represent the interaction between aorta and stent. The deformed geometry was then obtained based on the deformed centerline and deformed surface vertices, as shown in Figure 11.

A brief description of the procedure is given below. With image segmentation and reconstruction, one gets a STL file with triangular facets and vertices describing the aortic geometry. The original centerline \( L_{\text{original}} \), obtained using the VMTK extension for 3D Slicer, is then modified to \( L_{\text{deformed}} \) according to \( L_{\text{deformed}} = i \cdot L_{\text{original}} + (1 - i) \cdot L_{\text{reference}} \), as shown in the left panel of Figure 11. Here \( L_{\text{reference}} \) is a straight line closed by two splines, which ensure a smooth transition; \( 0 < i < 1 \) is defined to represent the stiffness of stent and aorta, and the aorta bending resistance. The surface is then deformed based on the deformed centerline, as shown in the right panel of Figure 11. A common orthogonal vector \( \vec{v}_{\text{rotation}} \) is defined for both the original surface and the deformed one, and it reads \( \vec{v}_{\text{rotation}} = \vec{d}_{\text{original}} \times \vec{v}_{\text{original}} \) for the original geometry. A vertex in the deformed surface can then be calculated based on \( \vec{v}_{\text{deformed}} = m \cdot (\vec{d}_{\text{original}} \times \vec{v}_{\text{rotation}}) \), with \( m \) the scaling factor to adjust the diameter of aorta. More details can be found in Ref. Neugebauer et al. (2016). Accordingly, the deformed geometries after intervention with different stents are shown in Figure 12.

4.2. CFD evaluation

The original pre-interventional geometry and its deformed versions can be found in Figure 12. The deformed geometries were exported as STL files, which were remeshed and further imported into the CFD solver for flow simulation. The above validated LES was used to resolve the flows in the pre-interventional geometry and the virtually deformed ones. We used the same boundary conditions as mentioned in Subsection 3.2, with flow rate of 13.2 mL/s at the inlet. The numerically obtained results are presented in Figures 13–15.

The color-coded streamlines in Figure 13 show that a stent with a diameter of 8 mm is inadequate to reduce the stenosis and jet flow with a large local flow can still be observed in the narrowing region. For stent diameter 12 or 16 mm, the jet flow disappears, with substantially reduced maximum velocity compared to the pre-interventional geometry. The velocity vectors, color coded with the velocity component \( W \), on different

![Figure 11. Virtual aortic deformation. Left: the schematic diagram of geometrical centerline deformation. Right: the schematic diagram of geometrical surface vertex deformation.](image-url)
cross-sections are provided in Figure 14. It presents a quantitative comparison of velocity distributions on on-stenosis planes within different geometries, as well as post-stenosis planes. On on-stenosis planes, the maximum velocities are 0.40, 0.35, 0.23 and 0.11 m/s respectively, decreased significantly from the pre-interventional geometry to the deformed ones. On post-stenosis planes, the jet flow, which leads to locally high WSS, can be found in both the pre-interventional geometry and the deformed one with a diameter of 8 mm. A much more uniform on plane velocity distribution is achieved in the geometries with larger stent diameter.

The WSS distributions are given in Figure 15. WSS describes the mechanical force generated by blood flow on the vessel wall, thus plays an important role in chronic adaption and remodeling (Humphrey & Schwartz, 2021). It is defined as $\tau_y = \mu \frac{du}{dy} |_{y=0}$, where $\mu$ is the dynamic viscosity of the flow, $u$ is the flow velocity along the wall and $y$ is the height above the wall. As shown in Figure 15, high WSS is observed in the stenosis region in the pre-interventional geometry and the deformed one with a stent diameter of 8 mm. After the stenosis, high WSS is also found in a part of the descending aorta due to the impact of high-speed jet flow (see Figures 13 and 14 for reference). A stent with diameter 16 mm enlarges the stenosis most and therefore leads to the smallest WSS in the same region. However, as this stent is larger than the size of the aorta, it also leads to a relatively large
Figure 14. Velocity vectors, color-coded with the component $W$, on different cross-sections. Time-averaged results. Top, on-stenosis plane; bottom, post-stenosis plane. From left to right: pre-interventional geometry, virtually deformed geometries with stent diameters of 8, 12, and 16 mm, respectively.

Figure 15. WSS on the pre-interventional and virtually deformed walls. Time-averaged results. From left to right: pre-interventional geometry, virtually deformed geometries with stent diameters of 8, 12, and 16 mm respectively.

WSS before the stent, compared to the case with a stent diameter of 12 mm.

4.3. Stent selection

To quantitatively compare the four cases with different stent diameter, the pressure drop and maximum WSS are given in Figure 16. It can be seen that the pressure drop is 119 Pa in the pre-surgical geometry and is reduced to 34 Pa and 28 Pa in the geometry with stent diameters 12 and 16 mm, respectively. For the maximum WSS on the aortic wall, the geometry with stent diameter of 12 mm provides the smallest value, 1.07 Pa. It is understandable that a larger diameter stent results in less flow resistance thus a smaller pressure drop, assuming that the aortic wall is always deformable. On the other hand, the size of the aorta wall and its nonlinear response to possible strain should also be considered. If a stent is too large for the aorta, it is conceivable that in addition to flow there will be an external mechanical force from the stent acting on the aortic wall.
Thus a stent with diameter 12 mm should be the optimal solution for the current patient-specific aorta, which agrees with the physicians’ independent choice in this case.

We further compared the virtually deformed geometry based on this optimal stent with the post-interventional one reconstructed from MRI images in Figure 17. Centerlines for both geometries were obtained and the distance (≤ 1.60 mm) between two centerlines is presented. Similarly, the spatial dependent diameters are also given, with a deviation less than 0.65 mm. It can be concluded that the virtually deformed geometry agrees with the clinically deformed one quantitatively. It should be noted that, in this study, the physicians chose a stent with diameter 12 mm independently and without input from the in silico modeling, which agrees with the prediction based on the combination of virtual geometry deformation and CFD simulation.

5. Discussion

5.1. In silico modeling

Image-based in silico stent implantation (D. Chen et al., 2018; Kan et al., 2021; Neugebauer et al., 2016; Pionteck et al., 2021) and CFD (Berg et al., 2018; Zhong et al., 2016) together provide a new framework for stent planning and interventional procedure evaluation. Besides a protocol for virtual geometry deformation, a CFD method is needed to accurately resolve the flows in the aortic geometries. However, blood flow in patient-specific aorta is complicated (Ku, 1997; Stein & Sabah, 1976). Laminar flow, turbulent flow and transition between them may coexist spatiotemporally. In our study, we firstly evaluated the accuracy of LES to predict such complicated flow. Two CFD methods, the LBM-based LES and DNS, in cooperation with flow MRI, were considered. Both phantom and in vivo validations show that the LBM-based LES, which keeps a balance between numerical accuracy and computational requirement, is a reasonable choice for resolving aortic flow. The validated LES was then used to predict the flows in virtually deformed geometries with different stent diameters. By comparing the flow fields, pressure drop, and maximum WSS, it was found that the optimal stent was the one with a diameter of 12 mm, which agrees with the physicians’ independent choice.

To restore blood flow, in addition to numerical methods, accurate geometry and boundary conditions are also important. Based on MRI scans, aortic geometry can be segmented and reconstructed from high-quality image slices (Avendi et al., 2016; Hadhoud et al., 2012; Kan et al., 2021). Furthermore, flow MRI is used for visualization and quantification of aortic flow. 2D flow MRI with through-plane velocity encoding is usually performed in clinical applications (Stankovic et al., 2014; Tanaka et al., 2010; Wentland et al., 2013). But the 2D flow measurement is affected by the selection of the cross-sectional plane. 4D flow MRI, alternatively, is able to obtain time-dependent 3D blood flow, which is resolved in all three dimensions of space and the dimension of time during the cardiac cycle. It can be used for the estimation of the flow pathways and the WSS. But 4D flow imaging takes a significant amount of time, which prevents wide clinical application. Thus for patient-specific in silico stent implantation, MRI and LES need to work together and both are indispensable. Particularly, MRI provides data for geometry and boundary conditions, while LES predicts aortic flows for further evaluation.
5.2. Limitations and future works

In this work, we validated the LBM-based LES with both phantom and in vivo experiments and provided a realistic example of the in silico stent implantation. There are still some improvements possible which could be considered in the future. Firstly, the aortic flow is unsteady, but we did not consider time-dependent boundary condition in our simulations. We argue that current boundary conditions are enough for us to compare different methods and provide results for stent evaluation. By modeling the realistic cardiac cycle, one may get more instantaneous flow information at the cost of longer computation time. Secondly, we assigned the flow rates to the vessel branches according to their cross areas. An alternative is the Windkessel model which considers resistance and capacitance of the vessel network. Thirdly, we used a fast geometric method to mimic the complex interaction between the aortic wall and the stent. Ideally, one would take into account the mechanical properties of the aortic wall and the stent, as well as the geometry of the stent, and model their interaction using the finite element method. Unfortunately, it is still a big challenge to get accurate orthotropic properties of the fiber-reinforced aortic wall and to model the contact problem numerically. Thus a simplified geometric method is a reasonable start and should be improved in the future for more realistic virtual stent implantation.

On the other hand, as an important part of in silico modeling, MRI provides information such as geometry and boundary conditions. Thus the image quality directly affects the flow field obtained. Therefore, MRI acquisition techniques and image post-processing still need to be optimized. Furthermore, although the traditional CFD can resolve the hemodynamics accurately, it is still time-consuming. For rapid surgical planning, other methods such as machine learning might be considered in the future.

6. Conclusion

As a congenital defect, CoA may cause many serious problems for patients if it is not treated in time and effectively. Stent intervention is a recommended therapy, but it remains challenging for physicians to find the optimal stent before treatment. In this study, we proposed a framework for personalized stent planning using in silico modeling, combining CFD and image-based virtual geometry deformation. We firstly compared the flow fields from LBM-based LES and DNS, and MRI for 3D-printed phantoms and in vivo. The validated LES was then used to resolve the flows in virtually deformed aortic geometries. Stents with three different diameters were considered. Based on the obtained pressure drop and maximum WSS, we concluded that a stent with a diameter of 12 mm was the optimal one for the patient. This agrees with the physicians’ independent choice. Our study shows that the proposed in silico stenting is a powerful tool and can be used to help clinicians to evaluate the surgical plans based on predicted results and to be able to select an optimal stent before intervention. Such methodology could also be extended to other stenosis, such as cerebral artery stenosis.

Ethics declarations

This article does not describe studies with human or animal subjects. The anonymous images used in this article were obtained from a clinical database. Informed consent of the patients that permits research use of their data has been obtained beforehand.

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