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From medical images to flow computations without user-generated meshes

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SUMMARY

Biomedical flow computations in patient-specific geometries require integrating image acquisition and processing with fluid flow solvers. Typically, image-based modeling processes involve several steps, such as image segmentation, surface mesh generation, volumetric flow mesh generation, and finally computational simulation. These steps are performed separately, often using separate pieces of software, and each step requires considerable expertise and investment of time on the part of the user. In this paper an alternative framework is presented in which the entire image-based modeling process is performed on a Cartesian domain where the image is embedded within the domain as an implicit surface. Thus the framework circumvents the need for generating surface meshes to fit complex geometries and subsequent creation of body-fitted flow meshes. Cartesian mesh pruning, local mesh refinement, and massive parallelization provide computational efficiency; the image-to-computation techniques adopted are chosen to be suitable for distributed memory architectures. The complete framework is demonstrated with flow calculations computed in two 3D image reconstructions of geometrically dissimilar intracranial aneurysms. The flow calculations are performed on multiprocessor computer architectures and are compared against calculations performed with a standard multi-step route.

Keywords

Image-based modeling; Level set method; Computational fluid dynamics; Cartesian grid methods

1. INTRODUCTION

Recent advancements in imaging techniques such as computed tomography (CT), magnetic resonance (MR), and transesophageal echocardiography (TEE), along with rapid increases in available computing power, have made possible the creation of realistic patient-specific 3D models derived from images that are not reliant upon functional geometric approximations. It is desirable (and with modern computational techniques and hardware, it

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is now feasible) to model the complexities associated with patient-specific geometries as accurately as possible in order to make predictions that have a real and significant impact. The standard route to performing image-based flow calculations [1–3] involves a series of processes that are executed in separate steps. First, geometries of interest are extracted from acquired image data through the process of segmentation, which provides the basis for geometric surface reconstructions. There are multiple commercial and open-source codes available to accomplish this, including the Vascular Modeling Toolkit (VMTK) [4, 5], which is primarily aimed at segmenting vascular and other closed tubular structures; 3D Slicer [6], which is a generalized medical image processing and visualization code; and others [1, 7]. Once the geometries of interest are segmented and reconstructed from the image data, they are typically fitted with a surface mesh (general tessellations; most commonly triangulations of the surface topology) in a subsequent step, and the surface mesh is then imported into a separate computational fluid dynamics (CFD) package such as Fluent™ (ANSYS, Inc., Lebanon, NH), in which a body-fitted volume mesh is created around the imported geometry. The generation of surface meshes from image segmentations and of the volume meshes that are produced to conform to the vessel geometries is a task that requires care on the part of the user. Poor quality surface and volume meshes can result in difficulties with the solution of the flow problem, ranging from inaccurate solutions to non-convergence of the solution process.

The overall goal of the present framework is to demonstrate a route to accurately compute flows through complex image-derived geometries in a way that does not require problem-dependent mesh generation. The basis of the current approach is to employ level set descriptions of surfaces embedded in Cartesian (but adaptively refined [8, 9]) grids. Since level set methods are extensively employed in image processing and are the outcome of several segmentation algorithms [3, 4, 10] and allow for sharp interface [11] flow calculations, a natural route for image-to-computation (see Fig. 1) can be constructed in this framework.

To date, several computational methods have been formulated for solving the equations of fluid motion (the Navier-Stokes equations) in the presence of complex boundaries using a Cartesian grid approach in place of body-fitted meshes [12], whereby boundary conditions are applied through modification of the scheme used to discretize flow variables near boundaries [11, 13–15] or through forcing terms [16–19] that are active in the vicinity of the immersed boundaries. The first of these approaches derive from the Immersed Boundary Method (IBM) [16], which was used to model the effect of an elastic material on fluid motion. A more recent variant of IBM is the discrete forcing approach, in which the physically based forcing term of the original IBM is replaced by a forcing derived from the numerical scheme itself, such that velocity boundary conditions are satisfied at prescribed locations [20, 21]. The second type is the sharp-interface approach, which directly incorporates boundary conditions into discretization operators near fluid-solid or fluid-fluid interfaces. Examples of this type of approach are the Immersed Interface Method (IIM) [22, 23], the Ghost Fluid Method (GFM) [14, 15, 24], the Sharp Interface Method (SIM) [13, 25, 26], and the Extended Finite-Element Method (XFEM) [27–29]. The Sharp Interface Method [13, 25, 26] solves a control-volume formulation of the governing equations such

that control volumes that are intersected by the interface are re-shaped to conform to the boundary.

A natural way of encoding geometric information so that it can be easily tracked is through the use of level set fields [30, 31], which implicitly define a boundary as the zero isocontour of a higher-dimensional signed distance function. A strong connection between level set-based Cartesian grid methods and image analysis emerges if one views images as implicit (intensity-based; typically gray-scale) representations of objects and the geometric surfaces that describe them. Furthermore, because of the Cartesian (voxelized) arrangement of image data, imaged surfaces can be described implicitly just as they are in other Cartesian grid-based methods. The surfaces of objects embedded in images can be identified through a variety of image segmentation techniques [10, 32–34], which partition image voxels into disjoint regions in which each voxel set is coherent in some predefined sense. These surfaces are generally defined by boundaries separating regions corresponding to an object's interior and exterior. Thus, many segmentation methods are formulated in terms of a level set field, and considerable research effort has been invested in the development of algorithms that robustly isolate imaged objects from their surroundings in a manner suitable for geometric reconstruction and modeling.

In this paper, we present a novel image-to-computation algorithm that combines a Cartesian grid incompressible Navier-Stokes solver with a single-phase active contours [10] image segmentation method, using level set representations to construct a unified formulation. The contour evolution algorithm, which is preprocessed with thresholding to remove outlying voxels that interfere with the segmentation process, produces smooth segments in a reliable and robust fashion. We also incorporate an object-labeling scheme that allows different surfaces found during the segmentation process to be distinguished from each other within the context of smooth contours, reducing the need for a closely cropped region of interest (ROI) and allowing for retention of contiguous features spanning the image domain. The Cartesian grid solver applies boundary conditions using a least squares-based ghost fluid scheme. The flow solver computations are carried out on a parallelized Cartesian grid framework, which is enhanced with local mesh refinement and mesh pruning to reduce the solver memory footprint. The generation of the locally refined mesh and the pruning of the resulting mesh to follow the boundary of the embedded geometry require no user intervention, as the base mesh is a simple cuboid. Once the imaged geometry is segmented and the level set field defining the embedded boundary is delivered to the simple cuboidal flow domain the mesh adaptation is performed automatically by using the level set function to refine and prune the mesh.

The remainder of this paper is organized into sections that outline the framework and its capabilities in detail. The first section gives an overview of the image-to-model framework. Next, the segmentation and flow solver capabilities are validated using two well-defined cases. Finally, the methodology is demonstrated on two human patient datasets by applying the complete framework to a CT angiography (CTA) image of an anterior communicating artery (ACoA) aneurysm (case 1) and a MR angiography (MRA) image of a middle cerebral artery (MCA) aneurysm (case 2), and analyzing the flow results.

2. FROM IMAGES TO COMPUTATIONS

2.1 Acquiring and Processing Images to Define Embedded Boundaries

2.1.1 The Level Set Method—In the current image-to-computation framework, level set representations are a unifying element of the segmentation and Cartesian grid flow solver algorithms. A level set field, $\phi(x)$, is a signed distance map for which an embedded boundary is coincident with the zero-contour of ϕ [30, 31, 35]. The sign of the distance function is conventionally defined such that points inside a surface have negative level set values, $\phi < 0$, and points external to the surface have positive values, $\phi > 0$.

The sign of the level set field is a useful quantity, because it offers a convenient means for classifying grid point types in the Cartesian flow solver, as well as a way to identify singly-connected regions occupied by an object. The facility for object identification is an important component of the present image-to-computation framework, as it enables the classification of multiple objects contained within an imaged region, in turn allowing for segmentation of a large ROI without the need for closely cropping the image domain or manually placing stopping regions to isolate the geometry being modeled. Using the object identification facility, desired objects can be retained in the flow domain, while extraneous features can be selectively excised. An algorithm for identifying and labeling objects that builds upon the level set representation is discussed in §2.1.3.

2.1.2 Active Contour Segmentation to Define Embedded Boundaries—

Segmentation is the process that defines object boundaries and makes surface modeling possible. Many segmentation algorithms have been developed to accomplish this, including cluster-based [32, 33, 36] and contour-based [10, 37, 38] methods.

Active contour evolution methods are based on early applications of elastic deformation theory to computer vision [39], and, unlike the discrete voxel grouping of cluster-based approaches, separate images into smoothly delineated regions directly. Contours are modeled as having elastic properties that serve to minimize the energy of mismatch between an evolving field and some underlying topology, which in this context is defined by the arrangement of image brightness patterns. Mumford and Shah [37] proposed an energy functional that decomposes the image domain Ω into piecewise smooth regions delineated by a segmentation contour C :

$$E(f, C) = \mu L(C) + \lambda \int_{\Omega} (I_o - I)^2 d\Omega + \int_{\Omega \setminus C} |\nabla I|^2 d\Omega. \quad (1)$$

In (1), $L(C)$ is the total arc length of the segmentation contour, and $\lambda > 0$, $\mu \geq 0$ are weighting parameters. The arc length penalty (regularization) term helps ensure that segmentation contours follow object boundaries smoothly, while the second term quantifies the mismatch between a representative function I and the original underlying image intensity I_o , and the third term constrains the spatial variation of I to be smooth within each segment.

Chan and Vese [10] later modified the M-S functional to delineate images into piecewise constant regions of average intensity rather than piecewise smooth regions of slowly varying intensity, eliminating the need for a smoothness constraint. They also recast the energy

minimization problem in terms of level sets, so that segmentation surfaces could be represented implicitly as zero-level isocontours of a signed distance level set field ϕ embedded in the Cartesian image space. The level set formulation also made possible the addition of a second regularization term that restricts the area of a segment along with the original curve length restriction, giving the Chan-Vese (C-V) energy functional

$$E(\varphi, c_1, c_2) = \mu \int_{\Omega} |\nabla \mathcal{H}_{\epsilon}(\varphi)| d\Omega + v \int_{\Omega} \mathcal{H}_{\epsilon}(\varphi) d\Omega + \lambda_1 \int_{\Omega} (I_o - c_1)^2 \mathcal{H}_{\epsilon}(\varphi) d\Omega + \lambda_2 \int_{\Omega} (I_o - c_2)^2 (1 - \mathcal{H}_{\epsilon}(\varphi)) d\Omega. \quad (2)$$

In (2), μ , v , and λ_i are weighting parameters and $H(\phi)$ is the Heaviside function of level set field ϕ , which can be approximated on a Cartesian mesh with grid spacing Δ as

$$\mathcal{H}_{\epsilon}(\varphi) = \frac{1}{2} \left[1 + \frac{2}{\pi} \arctan \left(\frac{\varphi}{\Delta} \right) \right]. \quad (3)$$

The constants c_i in the C-V functional represent the average brightness intensity in each segmentation region i , and are defined as

$$c_1 = \frac{\int_{\Omega} I_o \mathcal{H}_{\epsilon}(\varphi) d\Omega}{\int_{\Omega} \mathcal{H}_{\epsilon}(\varphi) d\Omega}, \quad c_2 = \frac{\int_{\Omega} I_o (1 - \mathcal{H}_{\epsilon}(\varphi)) d\Omega}{\int_{\Omega} (1 - \mathcal{H}_{\epsilon}(\varphi)) d\Omega}. \quad (4)$$

Euler-Lagrange minimization of (2) leads to a level set evolution equation

$$\frac{d\varphi}{dt} = \delta_{\epsilon}(\varphi) \left[\mu \nabla \cdot \left(\frac{\nabla \varphi}{|\nabla \varphi|} \right) - v - \lambda_1 (I_o - c_1)^2 + \lambda_2 (I_o - c_2)^2 \right]. \quad (5)$$

which acts on the $\phi = 0$ segmentation contour by making use of a regularized delta function

$$\delta_{\epsilon}(\varphi) = \mathcal{H}'_{\epsilon}(\varphi) = \frac{1}{\pi} \frac{\Delta}{\Delta^2 + \varphi^2}. \quad (6)$$

The delta function can also be summed over the voxels (i) in the image to estimate total segmentation surface area for each time step of contour evolution as

$$A_s \cong \sum_{i \in \Omega} \delta_{\epsilon}(\varphi_i). \quad (7)$$

so that the change in total surface area A_s between time steps can be used to define a stopping criterion.

In this work, the level set-based active contours approach of Chan and Vese was adopted due to its ability to reliably produce smooth segmentation surfaces – particularly when combined with pre-processing steps described in the next section. Furthermore, casting the segmentation problem in a level set formulation is central to the present method, as it directly yields the implicit surface representation required by the Cartesian grid solver. However, it should be noted that, while an emphasis has been placed on the active contours segmentation method in particular, any level set-based approach that gives an accurate geometric representation could be applied within the current framework.

2.1.3 Deriving Level Set Information to Supply to the Flow Solver—This section represents the crux of the image-to-model portion of our framework, and gives an outline of the complete set of steps involved with converting imaged data to modeled surfaces for use in flow simulations. The entire procedure, as illustrated in Fig. 1, is demonstrated, starting with a raw image, then through pre-processing, segmentation, and object identification, ending with a 3D reconstruction of an intracranial aneurysm.

One of the primary advantages of the active contours method described in the previous section §2.1.3 is its global, semi-automatic nature – i.e. once provided with the correct parameters, active contours will generate smooth surfaces wherever the given domain Ω satisfies the constraints defined by Equation (5), without further intervention required on the part of the user. Unfortunately, the method's global nature is also one of its disadvantages, as it leads to contour evolution being sensitive to the presence of multiple regions of different brightness levels within the image domain. This sensitivity is due in part to the two-phase approach of Equation (5); contour evolution is driven in large part by average intensity values calculated in two evolving regions of Ω . Thus, if the object of interest is bright, low-intensity objects in Ω will act to steer the evolving contour away from the desired segmentation surface. Conversely, if the object of interest has low intensity levels, then bright objects in the image will negatively affect contour evolution. Because this situation will most likely be encountered when segmenting real images, the active contours method must be enhanced with pre-processing techniques to ensure adequate robustness.

The current framework handles the robustness issue in two ways. First, the image is cropped to isolate the ROI as much as possible (Fig. 1(a)), removing many of the features of the original image domain that have intensity values differing significantly from the object to be reconstructed. This also improves efficiency in cases like the present IA geometries, which only occupy a small part of their respective image domains. Second, intensity thresholding is used, so that voxels possessing brightness intensities within a certain range are identified and pruned from the segmentation domain (Fig. 1(b)). Active contour evolution thus takes place on the remaining subset of voxels Ω_s identified by the thresholding operation. This procedure is found to significantly reduce the global dependence of the segmentation contour on imaged objects defined by intensity values that differ greatly from the average intensity in the ROI. Note that this step of identifying an ROI to focus the flow solver application involves user intervention and expertise.

One challenge that arises when segmenting with active contours on a pruned image domain after thresholding is that Ω_s is no longer rectangular in nature. In fact, Ω_s may be comprised of several disconnected, irregularly shaped portions of the original image domain Ω ; and evolution of Equation (5) must proceed from an initial level set field that exists everywhere in Ω_s . To handle this situation, a level set initialization approach is adopted in which Ω_s is populated with multiple spherical seeds defined by

$$\varphi(\mathbf{x}) = \left| \prod_{i=1}^3 \sin\left(\frac{\pi x_i}{d_s}\right) \right| - \frac{1}{2}, \quad (8)$$

where x_i are spatial coordinates in each of the three dimensions of image Ω and d_s is level set seed diameter. The result is a field of $\phi = 0$ spheres, each having diameter d_s and spaced d_s apart, embedded in Ω_s (Fig. 1(c)). This multiple seed approach ensures that all portions of Ω_s are properly initialized, and that evolution of Equation (5) may proceed in each part of Ω_s independently as necessary. Application of the technique indicates that neither the speed nor the accuracy of active contours is sensitive to initial seed size, provided that the seeds are small enough to occupy (at least in part) all regions of the thresholded domain while still being large enough to define coherent interior and exterior regions. Given voxel grid spacing Δx , in practice $d_s = 5 \Delta x$ was found to be a reliable initial seed diameter on a range of images.

While thresholding helps steer segmentation contours toward desired object boundaries, it is still possible that multiple objects, some of which will not be needed for modeling, will be segmented in Ω_s . For instance, in the case of the CTA of the ACoA aneurysm geometry, several objects in the ROI (e.g. the internal carotid arteries) have similar intensity levels, and thus show up in the final segmentation result (Fig. 1(d)). This issue is resolved by incorporating an object-labeling scheme [40] that allows singly-connected regions found during the segmentation process to be distinguished from each other while maintaining smooth contours. This amounts to a tagging operation, which gives a unique label to each contiguous object within the image domain (Fig. 1(e)).

The object labeling procedure is initialized by first assigning all points in the image domain with a null object tag. The domain is then scanned in its natural ordering until a point is found to be located inside of an object – a state that is easily identified by the sign of a voxel's (negative) level set value. Once found, this point is tagged with an object number of 1 (Fig. 2(a)). All of the tagged point's neighbors are then scanned, and any neighbors that are found to have both the same level set sign and a null tag are also tagged with an object number of 1 (Fig. 2(b)). Once found, all these newly tagged neighbor points scan *their* neighbors, similarly tagging any neighbors that are found to be inside the object with the number 1. This iterative neighbor tagging continues until no null-tagged neighbors remain to be found within a contiguous object. The procedure then goes back to the last null-point found in the natural ordering and scans for the next point that is both inside an object and in possession of a null tag (Fig. 2(c)). Any points lying inside this object are tagged with an object number of 2, and so on. The algorithm continues in this fashion until all objects in Ω have been located and numbered (Fig. 2(d)). Classifying the domain into a set of objects in this way allows the modeled geometry to be isolated without the need for a closely cropped ROI; objects to be included in the model can easily be identified and retained, and others can be removed. It also provides a convenient mechanism for de-noising the segmentation field: Tagged objects that do not meet, for example, some predefined size criterion can be removed from the final segmentation result.

Once all desired objects have been isolated and extracted from the image domain, their level set fields are mapped to a flow solver mesh with local mesh refinement and pruning capabilities (described in the next section) for CFD simulation (Fig. 1(f)). A complete overview of the algorithm used to derive embedded boundaries from images and communicate them to a flow solver can be summarized in the following set of steps:

1. Crop the image to isolate the region of interest (Fig. 1(a)).
2. Prune the domain by thresholding intensity to remove outlying voxels from the segmentation process (Fig. 1(b)).
3. Initialize the pruned domain with spherical level set seeds (Fig. 1(c)).
4. Perform segmentation via active contours evolution on the pruned domain (Fig. 1(d)).
5. Tag connected regions as distinct objects using unique labels (Fig. 1(e)).
6. Re-initialize [30] the level set fields of desired objects to convert them to signed distance functions (Fig. 1(f)).

Note that in the above algorithm, the user is not required to generate meshes to conform to the embedded surfaces nor is there a need to generate volume meshes to conform to the surfaces in order to compute flow.

2.2 The Flow Solver with Embedded Boundaries

This section of the paper builds from previous work in which techniques for solving transport phenomena in complex domains (with stationary or moving boundaries) were developed in a fixed Cartesian grid Eulerian framework [8, 11, 41]. The challenge of developing techniques for treating the embedded boundaries as sharp entities has been addressed in several previous publications [8, 11, 42, 43].

2.2.1 Cartesian Grid Method—The current work is concerned with computing fluid motion in geometries defined by level sets extracted from images. The flow field is obtained by solving the incompressible Navier-Stokes equations:

$$\nabla \cdot \mathbf{u} = 0, \quad (9)$$

$$\frac{\partial \mathbf{u}}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u} = -\nabla p + \frac{1}{\text{Re}} \nabla^2 \mathbf{u}. \quad (10)$$

Here, $\mathbf{u}$ and p are the fluid velocity vector and pressure, and $\text{Re} = UL/\nu$ is the Reynolds number. U and L are characteristic flow velocity and length scales, and ν is the kinematic fluid viscosity. The governing equations are advanced in time using a 2nd-order four-step fractional step algorithm to segregate the pressure from the velocity [44]. The non-linear and viscous terms are integrated temporally using the 2nd-order explicit Adams-Bashforth and semi-implicit Crank-Nicolson schemes, and all spatial derivatives are approximated using 2nd-order central differencing. The variables are stored at mesh cell centers with the exception of a set of cell face velocities (satisfying the divergence-free condition over each mesh cell) that are used to construct the advection terms.

Boundary conditions on embedded boundaries (defined by the zero-contours of the embedded narrow-band level set field) are applied using a least-squares formulation of the sharp interface method. In this approach, a three-dimensional quadratic least-squares method is used to extrapolate flow variable values to a set of ghost nodes immediately outside the

flow domain [44]. The least-squares formulation allows one to obtain locally 2nd-order spatial convergence rates on arbitrarily shaped domains. The implicit filtering inherent to least-squares methods also enhances the robustness of the approach when geometries with noisy surfaces are simulated. A detailed analysis of the current interface treatment is described in [44].

2.2.2 Mesh Structure—In the case of internal flows in tortuous geometries, a straightforward Cartesian mesh implementation imposes an unnecessarily large memory footprint due to the nominal cuboidal shape of the flow domain forced by the Cartesian grid layout. Furthermore, as the flow solver operations only occur in the portion of the mesh that corresponds to the fluid phase (i.e. in the interior of the embedded objects), retaining the extraneous mesh outside the flow domain may induce severe load imbalances in a parallel algorithm. To alleviate these difficulties, the current flow solver operates on a Cartesian base mesh that is enriched with local refinement and mesh pruning [44]. During the set-up phase of the simulation, Cartesian base mesh cells that are not required to complete the calculation are discarded. Local refinement is achieved on the pruned Cartesian mesh using a forest-of-octrees approach [2], where each base mesh cell holds the root of a fully-threaded octree, and the nodes of the octree with no children correspond to fully refined mesh cells. As an example, the pruned and refined mesh resulting from a 90° bent tube geometry is shown in Fig. 3. The pruned Cartesian background mesh follows the shape of the tube, and mesh refinement is imposed in a small band around the tube surface. In order to facilitate the construction of discrete operators, the mesh satisfies a 2:1 balancing constraint where no mesh cell has a neighboring cell across a face, edge, or corner that is more than one level coarser or finer. The 2:1 balance constraint is imposed through the use of the highly scalable Prioritized Ripple Propagation algorithm [2, 45].

3. VALIDATION

The flow solver and the segmentation algorithm comprise the two principle components of the complete image-to-model framework, and thus require thorough validation. This section validates each component by applying it to a well-defined geometry and testing for accuracy. The flow solver is validated by comparing its results with experimental results of flow through a bent tube. The segmentation method is validated against measurements of an anatomically realistic cerebral aneurysm phantom.

3.1 Validation of the Flow Solver

Flow in a tube bent through a ninety-degree angle is used to demonstrate the ability of the current approach to capture flows in tortuous tubes where secondary flows can occur. Van de Vosse *et al.* [46] performed laser Doppler velocimetry experiments to obtain the center-plane axial velocities at a set of angles around a tube bend. To match the experimental conditions, the Reynolds number based on the tube diameter and the mean inlet velocity was set to 300. The internal diameter of the tube is 1, and the radius of curvature of the pipe bend is 6. Extensions of 1 diameter in length were added to the start and end of the bend. A fully developed parabolic profile was prescribed at the inlet boundary, and a convective outflow condition was prescribed at the outlet boundary. Because nearly the entire domain contains

vorticity, solving on a locally refined grid would not prove particularly useful. Therefore, the computations were carried out on a base grid on which the grid spacing was set to $\Delta x = 0.02$. This mesh was sufficiently fine to obtain grid-independent results.

The flow field was solved on a mesh that was pruned to only retain grid cells in the fluid or immediately adjacent to the tube's boundary Fig. 4(a). Streamlines indicating the secondary flow in the tube are plotted over contours of the velocity magnitude on the center-plane in Fig. 4(a). The axial velocity on the center-plane at the start of the outlet extension is plotted in Fig. 4(b) along with the experimental values obtained by Van de Vosse *et al.* It is observed that there is excellent agreement between the current computational results and the experimental results. It is clear that the proposed pruning algorithm yields a significant reduction in the required base grid for the current case and demonstrates the added benefit that mesh pruning provides to the current Cartesian discretization method for the tortuous geometries found in many biological systems.

3.2 Validation of the Segmentation Approach

Estimating the accuracy of the segmentation method used to construct a model from *in vivo* image data such as an IA is difficult in practice, because there is no way to directly measure the object being imaged. It is, however, possible to validate the segmentation method by applying it to a similarly imaged geometry with dimensions that are known *a priori*. In this work, the chosen segmentation approach is tested by applying it to a CTA image of an anthropomorphic intracranial vascular flow phantom (Shelley Medical Imaging Technologies, Ontario, Canada) containing the entire circle of Willis and a large saccular aneurysm of the anterior communicating artery (Fig. 5).

The phantom was imaged at the University of Iowa Hospital and Clinics (UIHC) using a Siemens Sensation 64 CT scanner, following scanning protocols for aneurysm patients [47]. The complete data set consisted of $249\ 512 \times 512$ -pixel slices, spaced 1 mm apart, with each pixel having dimensions $\Delta x = \Delta y = 0.309$ mm. Following the steps outlined in §2.1.3 the aneurysm geometry was isolated by cropping the image to an $84 \times 128 \times 64$ voxel subregion, then thresholding the subregion to exclude voxels with an intensity level lower than 220. The thresholded subregion was then segmented via active contour evolution with parameters $\lambda_1 = \lambda_2 = 1$, $\mu = 0$, and $\nu = 10$ until Equation (5) reached a state of convergence defined by a change in total segmentation surface area $\Delta A_s < 1$. Once segmented, the aneurysm geometry was identified with the tagging operation in §2.1.3, and everything else in the subregion was removed.

A comparison of the final segmentation result and the phantom geometry is given in Fig. 6. The aneurysm bulb was measured horizontally in the X-Z plane and vertically in the Y-Z plane to be 9.44 mm and 9.33 mm, respectively, giving an error of 5.6–6.1% compared with the bulb diameter of 10 mm reported in the manufacturer's specifications. The height of the bulb was measured from the narrowest part of the aneurysm neck to be 13.1 mm, which yields a 0.77% error. The left anterior cerebral artery diameter produced by our segmentation also agreed well with manufacturer's specifications, with a diameter of 3.04 mm (2.3% error). Finally, the neck was measured across its narrowest portion to be 4.06 mm (16% error). The error in the neck region was substantially higher than in other measured

regions, but the value is nevertheless comparable with measurements reported previously [47].

Overall these results compare closely with those obtained using established software (VMTK), and they lend confidence in the method due to the challenging nature of the phantom image compared with what is expected from real CTA images. Table 1 summarizes several metrics used to assess image quality. Of particular note is the low contrast in the phantom image – there is only a 9.7% difference between the intensities of the object and background segments. This is clearly visible in Fig. 7(a), which shows a slice near the center of the segmentation subregion. Re-scaling the intensity range on the same slice (Fig. 7(b)), with the corresponding slice of the segmentation surface overlaid) makes the geometry more discernable, but also highlights the noise present in the background of the image. The low contrast in the image therefore makes the delineation of the contours of the phantom challenging. Despite the low contrast, the current approach was successful in reconstructing the phantom geometry (Fig. 6, Fig. 7(c)) semi-automatically without user-defined fiducial points, giving confidence in the method's ability to segment data sets that exhibit better contrast.

4. TESTING THE METHODOLOGY ON REAL DATA: COMPUTATION OF FLOW IN THE INTRACRANIAL ANEURYSM

In this section, the proposed methodology is applied to extract the flow characteristics of two intracranial aneurysms imaged *in vivo*: A CTA of an ACoA aneurysm (case 1) and an MRA of a left MCA aneurysm (case 2). Results are compared with cases obtained via the standard route using a combination of three packages, viz. VMTK, Gambit™ (for grid generation; Ansys, Inc., Lebanon, NH) and Fluent™, starting from the same two image data sets.

4.1 Case 1: Anterior Communicating Artery Aneurysm from CTA

4.1.1 Image-to-Computation Setup and Execution—In the modeling steps of the image-to-computation framework, the ACoA aneurysm geometry was reconstructed from a CTA data set acquired at UIHC with a Siemens Sensation 64 scanner, following the algorithm in §2.1.3. The data set consisted of 319 512×512 -pixel slices, spaced 0.5 mm apart, with pixel dimensions $x = y = 0.390625$ mm. The geometry was isolated by cropping the image to a $128 \times 128 \times 64$ voxel subregion and thresholding to exclude voxels with an intensity level lower than 130. Active contour parameters were set to $\lambda_1 = 1.25$, $\lambda_2 = 1$, $\mu = 1$, and $\nu = 100$, and Equation (5) was evolved until $A_s < 1$. Once segmented, the aneurysm geometry was identified and isolated with the tagging operation described in §2.1.3.

The 3D reconstruction of the ACoA aneurysm turned out to be considerably smoother than that of the phantom geometry in §3.2, likely due to the higher image quality exhibited by the real CTA compared with the phantom CTA. As can be seen in Table 1, the contrast is significantly greater than it was for the phantom geometry, with the aneurysm being 96% brighter than the background (compared to 9.7% for the phantom). The signal-to-noise ratio

is not as high as it was for the phantom, due to the lower overall intensity, but the improved contrast gives a contrast-to-noise ratio that is 78% greater than that for the phantom. This leads to a decreased sensitivity to noise compared to the phantom segmentation, yielding a smoother surface.

The final extracted aneurysm geometry is shown in Fig. 8(a), along with the boundary conditions applied to the anterior cerebral arteries (ACA). Flow inlets are located at the proximal ends of each ACA (segment A1) and outlets are located at the distal ends (segment A2) as shown. A uniform flow profile was assigned at both inlets with $U_{inlet\ 1} = 0.72U_{inlet\ 2}$, where $U_{inlet\ 1}$ and $U_{inlet\ 2}$ were based on equal mass flow rates at both inlets in the comparison case (hereinafter referred to as V-G-F). A convective outflow condition was applied to both outlets, with each given a mass split of 50% to match the 50/50 outlet split condition specified in the V-G-F case.

The present simulation was performed at a physiologically realistic local Reynolds number of 219, with the local Reynolds number being matched to the V-G-F case Reynolds number by calculating a nominal diameter and flow rate at the left A1 cross-sectional location shown in Fig. 8(a) and Fig. 8(c) for each of the geometries. The base mesh spacing was set to 0.2 on a $17 \times 19 \times 24$ domain (prior to pruning), and 2 additional levels of refinement were applied during the simulation to give a minimum grid spacing of $\Delta_{min} = 0.05$ and a total of 2,927,701 volume elements. An unsteady flow simulation was run in parallel on 256 cores (shown by coloration in Fig. 8(b)) of the Helium cluster at the University of Iowa's High Performance Computing center for 10,000 time steps, which was found to be more than sufficient to obtain a steady-state solution (no change in the flow field was observed after 8000 time steps). Total wall clock time for the simulation was 5606 seconds. For comparison, the V-G-F case was meshed with 1,710,048 tetrahedral volume elements, and a direct steady solution was obtained on 50 cores of the Helium cluster in ~ 1800 seconds.

Grid independence of the flow solution was tested by comparing results at three levels of resolution: $\Delta_{min} = 0.1$, $\Delta_{min} = 0.05$, and $\Delta_{min} = 0.025$, with three levels of local mesh refinement applied in each case. Velocity magnitude distributions were found to be similar between the three levels of resolution (Fig. 9), with small velocity magnitude errors between each mesh size (Table 2). Average wall shear stress and surface pressure on the aneurysm bulb surface were also calculated at each grid level (Fig. 10), demonstrating convergence with small errors between medium and fine grid resolution levels (Table 3).

4.1.2 Discussion of the Results—Streamlines generated in the aneurysm geometry at steady state for our method are shown in Fig. 11(a), with those generated for the V-G-F solution shown in Fig. 11(b). Pressure contours are displayed on the streamlines to provide an interpretation of the flow's acceleration along its trajectory.

In both cases, the streamlines in the inlet sections of the flow indicate the presence of secondary flows in the curved ACA vessels similar to the secondary flow observed in the bent tube case presented in §3.1. The two inlet jets merge at the aneurysm bulb and induce a strongly tortuous streamline pattern; and a separating manifold (separatrix) exists for which streamlines originating from an inlet do not become entangled in the bulb, but instead flow

directly to an outlet. This phenomenon is most pronounced between right A1 and left A2, where a large number of fluid trajectories appear to bypass the bulb completely in both cases, and it appears that fluid that does enter the bulb is more likely to exit through right A2.

To compare the results obtained with the current framework with those computed using the V-G-F approach, the surface pressure and wall shear stress are computed using a third-order least-squares reconstruction procedure. The aneurysm geometries' surface pressure behaviors appear to be quite similar between our case and the V-G-F case, as illustrated by the surface pressure plots shown in Fig. 12. In both cases the surface pressure decreases quickly in response to the strong acceleration of the two inlet streams from left and right A1 just before they merge at the aneurysm bulb. Steady circulating flow in the bulb itself maintains a relatively constant pressure there, and then the pressure drops once more as fluid accelerates toward the outlets through left and right A2. The final pressure drop is most pronounced through right A2 in both cases, as it narrows to a smaller diameter than left A2.

Wall shear stress was also compared at the surface of each of the aneurysm geometries being compared. Wall shear stress is defined as the magnitude of the tangent component of the viscous stress on the aneurysm surface

$$WSS = \|\mathbf{t} - (\mathbf{t} \cdot \mathbf{n})\mathbf{n}\|, \quad (11)$$

where

$$\mathbf{t} = \boldsymbol{\tau} \cdot \mathbf{n}, \quad (12)$$

and

$$\boldsymbol{\tau} = 2\mu \mathbf{D} \quad (13)$$

is the shear stress, defined in terms of the fluid's viscosity D and the rate of deformation tensor μ . The wall shear stresses obtained from the present computations and the V-G-F approach are shown in Fig. 13. Wall shear stress has a similar distribution in both our result and that of the V-G-F case, particularly in the parent vessels, though a notable difference is a lower overall shear stress in the aneurysm bulb in our case. There are two major factors that could cause this difference to be observed. First, our method utilizes second-order spatial discretization; the precise order of accuracy of the FluentTM results is difficult to ascertain but it is unlikely that second-order accuracy is achieved. Second, VMTK utilizes Taubin's non-shrinking algorithm [48, 49] to produce smoothed surfaces from faceted ones during the modeling process, which in this case allowed some surface corrugations to remain. On the other hand, the current segmentation method produced a smooth surface directly. Smoothness significantly affects shear stress calculations because of the strong effect it has on the behavior of the fluid layer near solid surfaces, and thus likely contributes to the differences observed between the two cases. On the other hand, second-order discretization combined with the denser mesh used in our calculation potentiates a more accurate result.

As a final qualitative comparison, in addition to the surface and streamline plots, the present results are also compared with those obtained using V-G-F by plotting contours of velocity magnitude on orthogonal slices through the aneurysm bulb (Fig. 14). There are distinct similarities between the two cases that can be seen in each slice, such as the stagnant regions near the exit from the bulb into left A2 visible in the Y- and Z-planes (Fig. 14(b) and (c)) and high-velocity jet visible at the bottom of the X-plane (Fig. 14(a)). In fact, the overall velocity magnitude distributions appear similar in both cases. One primary difference between the two cases appears to be in the magnitudes of the gradients between high- and low-velocity regions; our result predicts compact regions of high velocity separated from other parts of the flow by high velocity gradients, whereas the flow velocity in the V-G-F case does not feature the same strong gradients.

While these qualitative observations help elucidate some of the similarities and differences between the current and V-G-F cases, it is also necessary to examine some quantitative measures to obtain a more complete basis for comparison. To this end, for each case three indices that are useful for quantifying IA characteristics were calculated: Average wall shear stress (WSS_{avg}) in the aneurysm bulb, low wall shear area (LSA) in the bulb, and the aneurysm's inflow concentration index (ICI) [50, 51]. For all three of these indices, it is necessary to define what constitutes the aneurysm bulb. To do this we adopted the convention reported in other works, where the ostium surface, or plane through the bulb opening, is defined by the location where a practitioner would clip the aneurysm for treatment. (The bulb surface defined in this way is highlighted in Fig. 15). While this is a visual judgment call, care was taken to closely match the ostium surface locations between the current and V-G-F cases.

Indices for the current and V-G-F cases are summarized in Table 4. WSS_{avg} was found in each case by calculating

$$WSS_{avg} = \frac{\sum_i WSS_i A_i}{\sum_i A_i} \quad (14)$$

in Tecplot 360™ (Tecplot, Inc., Bellevue, WA) over the surface elements defining the bulb region. The LSA index was calculated as the percentage of the bulb's surface area covered by abnormally low WSS values; "abnormally low" was defined in the manner suggested in [51] as WSS values less than the 15.87th percentile of WSS in the parent vessels supplying the aneurysm. ICI gives a measure of the concentration of inflow to the aneurysm bulb relative to total flow through the parent vessels as defined by Cebal *et al.* [50]:

$$ICI = \frac{Q_{inflow} / Q_{PV}}{A_{inflow} / A_{OS}} \quad (15)$$

In Equation (15), $Q_{inflow} = \int_A \mathbf{u} \cdot \mathbf{n} dA$ is the fluid flow rate *into* the aneurysm bulb through the ostium surface, Q_{PV} is the flow rate through the left and right A1 parent vessels, A_{OS} is the area of the ostium surface, and A_{inflow} is the area of the portion of the ostium surface through which fluid flows into the aneurysm bulb.

As can be seen in Table 4, the first two indices agree closely between the two cases. WSS_{avg} gave an error of 6.51%, while agreement was quite strong for the LSA index, with an error of 0.065%. The larger error in WSS_{avg} is possibly due to slight differences in surface smoothness and segmented geometry between the two cases. The ICI index showed less agreement, with our result giving an ICI index 11.20% lower than that of the V-G-F case. The primary reason for this difference is the higher percentage of flow entering the bulb in the V-G-F case. The inflow area A_{inflow} is similar for both cases (42.1% of the ostium surface area A_{OS} in our case and 44.1% in the V-G-F case); however, the percentage of flow entering the bulb through the inflow area is 63.4% in our case while it is 74.8% in the V-G-F case. This indicates that more of the flow bypasses the bulb and proceeds directly through the parent vessels to the outlet in our case.

4.2 Case 2: Left Middle Cerebral Artery Aneurysm from MRA

The second test case evaluated was a left MCA aneurysm reconstructed from an MRA image acquired by a Philips Medical Systems MR scanner. This image was chosen because of its geometric differences from the previous ACoA aneurysm image, and because of the challenges presented by way of its different modality. The data set consisted of $125\,512 \times 512$ -pixel slices, spaced 0.7 mm apart, with pixel dimensions $x = y = 0.3125$ mm. The aneurysm geometry was isolated by cropping the image to a $64 \times 64 \times 64$ voxel subregion and then thresholding to exclude voxels with an intensity level lower than 100. Geometric reconstruction followed the steps outlined in the previous section §4.1. The simulation was performed at a Reynolds number of 327, matched to the Reynolds number of the corresponding V-G-F case at corresponding MCA inlet regions. The base mesh spacing was set to 0.2, and 2 additional levels of refinement were applied during the simulation to give a minimum grid spacing of $\Delta_{min} = 0.05$ and a total of 7,371,553 volume elements. The unsteady flow simulation was run in parallel on 256 cores for 30,000 time steps to steady state.

The modeled geometry is comprised of a saccular aneurysm of the sphenoidal segment M1 of the MCA, proximal to the insular segment M2. It differs from the ACoA aneurysm geometry in that there is only one parent vessel instead of two, and the MCA parent vessel has a diameter that is $\sim 24\%$ larger than the ACA parent vessels supplying the ACoA aneurysm (2.33 mm compared to 1.88 mm). Flow characteristics also differ, with a 50% increase in the Reynolds number in the MCA parent vessel over that of the ACA parent vessels of the ACoA aneurysm. Both the current and V-G-F cases were prescribed with velocity inlet conditions and 50/50 mass split outflow conditions distal to the bifurcation at segment M2.

Comparisons between the current and V-G-F cases are given in plots of surface pressure and wall shear stress (Figure 16) and in the table of indices (Table 4). Normalized velocity magnitudes are also compared in slices parallel to and perpendicular to the direction of bulk flow through the aneurysm in Figure 17. In each case, surface plots show pressures and wall shear stresses to have small magnitudes on the proximal surface of the aneurysm bulb, where stagnation occurs due to the abrupt expansion of the MCA parent vessel at the base of the aneurysm. Meanwhile, flow impinging on the distal surface yields higher surface

pressures and shear stresses in the downstream region of the aneurysm wall. This behavior is further elucidated by the contours of velocity magnitude shown in slices parallel to the bulk flow in Figure 17(b). (Slice location within the vessel is shown in Figure 17(a).) In these “parallel” slice plots, the direction of bulk flow proceeds from right to left, though it should be noted that localized regions of the velocity field have significant out-of-plane components in general, due to the vessel’s curvature and the flow’s complex 3D nature. In Figure 17(b) flow separation is clearly visible at the base of the aneurysm on the upstream side in both cases, leading to the low surface pressures and wall shear stresses observed in the same region in Figure 16. There is also a center of rotation visible near the middle of the aneurysm bulb in both cases, with clockwise rotation in the slice plane being generated by the bulk flow’s momentum as it passes through the parent vessel from right to left adjacent to the ostium surface.

Figure 17(c) illustrates normalized velocity magnitude values in slices through the aneurysm that are orthogonal to the direction of bulk flow in each case (slice location illustrated in Figure 17(a)). In both cases the velocity magnitude is large near the left wall of the parent vessel and small at the center of rotation near the middle of the aneurysm bulb. The high-velocity region near the left wall comes about because of the curvature of the parent vessel; the centripetal component of the bulk flow’s curved path points toward the right in this view, thus the right wall is nearest to the vessel’s center of curvature in this slice. As such, the fluid’s momentum carries it away from the right-hand wall and toward the left-hand wall as it makes its way through the lumen of the vessel. Fluid that is entrained into the aneurysm bulb thus enters from the left side, generating clockwise rotation about the low-velocity center visible near the middle of the bulb.

Table 4 compares the three indices evaluated previously, namely WSS_{avg} , LSA, and ICI, between the current and V-G-F cases. Notable is the fact that WSS_{avg} values are significantly higher than they were in the previous case. This is partially due to the higher Reynolds number of the flow in the MCA overall, but it is also due to the fact that the aneurysm’s size compared to its parent vessel(s) is significantly smaller than it was in the previous ACoA case. The result is that expansion from the parent vessel into the aneurysm bulb is significantly reduced, leading to the entrained flow maintaining a higher velocity than it would if the bulb was markedly larger in diameter than the parent vessel. This is likely also the reason for the current case’s smaller LSA index compared to that of the previous ACoA case; more of the MCA aneurysm’s surface is subjected to WSS values similar to those found in its parent vessel because the entrained flow’s velocity is not as significantly diminished by a large expansion. Along similar lines, the current MCA case has a small ICI compared to the previous ACoA case because much of the flow through the parent vessel proceeds past the relatively smaller aneurysm without becoming entrained.

The percentage difference in the MCA case between our method and the V-G-F method for each index turned out to be 8.34%, 18.82%, and 20.11%, respectively. The differences between the two methods are greater than they were in the previous ACoA aneurysm case; however, this is attributable to greater differences between the segmented geometries produced by the two methods in the present case (Figure 19). While the MRA image containing the present MCA geometry has superior contrast, signal-to-noise, and contrast-to-

noise ratios compared to the CTA image of the ACoA aneurysm evaluated previously (Table 1), it lacks *sharpness*. This is illustrated in Figure 20(b), which shows voxel values of image intensity field in a constant y-plane just upstream from the aneurysm (the plane's location is illustrated in Figure 20(a)). The segmentation contour from the current method on this slice is shown in black, with the V-G-F segmentation contour shown in red. Due to the lack of image sharpness, the true locations of geometric boundaries of interest are segmented differently by the two approaches. The current active contours approach is semi-automated, and produces a result that depends on image characteristics like average intensity and gradient of intensity. The V-G-F method also employs the level set segmentation technique in the VMTK software; level set segmentation in that case was performed using a colliding front approach for the aneurysm sac and a fast marching approach for the parent vessels followed by smoothing of the geometry using a Taubin non-shrinking filter. The result of these operations in the V-G-F method as opposed to the present method is that there are discernable differences in geometric features, both in the parent vessel as well as in the aneurysm. First, as shown in Figure 18, contrasting the views of the geometries in Figure 18(a), the vessel proximal to the aneurysm sac is narrower in the V-G-F case than in the present case; and second, the aneurysm sac is segmented to be larger in the V-G-F case than in the present case. The view in Figure 18(b) shows a significant narrowing of the vessel proximal to the sac in the V-G-F case, which is not found in the segmentation using the current method. This narrowing of the vessel implies a higher average velocity of the flow past the aneurysm in the parent vessel; however, since the aneurysm is somewhat larger in the V-G-F case the flow inside the cavity is accommodated in a larger volume implying a moderation of flow speeds in the sac itself. The differences in segmented geometry are actually rather small if viewed in terms of the voxelized intensity fields, as shown in Figure 19. Figure 19(a) (right) shows the intensity field on the indicated plane (Figure 19(a) (left)) in the image domain. The red line is the segmentation due to VMTK and the black line is due to the current approach. The segmentations are off by about one voxel, relying on a rather diffuse intensity field. In the case of the aneurysm sac, Figure 19(b) (left) shows the section under consideration and the intensity field in that plane is shown in Figure 19(b) (right). The segmented sac boundaries due to VMTK (red) and the present active contour approach (black) are seen to be off by one voxel as well. These geometric differences are reflected in Figure 18, with the V-G-F vessel being narrower and the sac larger than those yielded by the present approach. The differences in the computed flow measures result from these differences in delineating the geometry using the two different approaches seeking to segment a rather diffuse image. Despite these geometric differences, however, the computed flow field magnitudes (as shown in Figures 16 and 17), patterns (such as separation and stagnation points in the planes shown in Figure 17), and measures such as the computed indices are in fairly good agreement.

5. CONCLUSIONS

In this paper, we have proposed an image-to-computation algorithm that is designed to minimize user intervention; in particular the user is not burdened by the intermediate steps of surface mesh generation to tessellate the solid geometry and the volumetric fluid flow mesh generation to conform to the surface mesh. The methodology of the algorithm builds

upon an existing Cartesian grid- and level set-based flow solver framework, which provides a natural and direct connection between imaged geometries and their related flow simulations. The entire flow solution process is executed in a parallel computing environment with additional gains in memory and compute time efficiencies due to a combination of adaptive mesh refinement and mesh pruning to follow the contours of the embedded boundary. The algorithm was demonstrated with unsteady flow computations through to steady state for two intracranial aneurysms obtained from CTA and MRA data, where image segmentation was performed using active contours and the resultant level set field was mapped to a flow solver mesh for CFD simulation. Comparison of the current approach with the commonly employed VTK-Gambit-Fluent route showed good agreement in the computed wall shear stress and pressure patterns on the aneurysm and vessel walls. Indices for measures of clinical relevance were also in fair agreement for both geometries considered despite the differences in segmented geometric details between the two techniques.

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Fig. 1.
Overview of the image-to-model framework

Fig. 2.

Illustration of the object labeling algorithm [40]. All pixels/voxels in Ω are initialized with a null tag. (a) Scanning proceeds along the natural ordering until the first pixel/voxel is found inside an object (defined by the sign of its level set value), and tagged with object number 1. (b) Unvisited neighbors falling inside the object are iteratively tagged with an object number of 1 until no untagged pixels/voxels remain inside the object. (c) Scanning continues from the pixel/voxel found in (a) until the next pixel/voxel falling inside an object is found and

tagged with object number 2. (d) The process continues until all objects in Ω are found and tagged

Fig. 3.

An example of a pruned Cartesian mesh with local refinement. In this figure, the Cartesian mesh is trimmed to closely follow the shape of a tube bent through a 90° bend and the mesh is refined immediately near the tube surface. The mesh is partitioned between 4 MPI processors as indicated by the coloring

Fig. 4.

Flow solver validation. (a) Flow through a 90° bent tube is solved on a pruned mesh, eliminating a large unnecessary portion of the domain; (b) the flow solver agrees closely with experimental results measured in the center plane of the tube at the end of the curved section

Fig. 5.
Phantom geometry (a), and measurements provided by the manufacturer (b)

Fig. 6.

Photos of the silicone phantom geometry (left) and similar views of the 3D reconstruction obtained using the current segmentation method (right). Measurements were taken of the aneurysm bulb height, bulb diameter, neck diameter, and diameter of the proximal aspect of the left anterior cerebral artery

Fig. 7.
Phantom CT and segment: image slice (a) scaled with the full dynamic range of the image;
(b) illustrates the segmentation contour overlaid on the same image slice, which has been
rescaled in [225,255] for clarity; (c) 3D reconstruction

Fig. 8.

The reconstructed ACoA aneurysm geometry using the current method: velocity inlets are prescribed in proximal segments A1 of the right and left ACA, and convective outflow conditions with a 50/50 mass split are assigned in segments A2 (a). Flow through the aneurysm geometry was computed on 256 processors (computational domain colored by processor number) of the Helium cluster, the University of Iowa's high performance computing facility (b). Our results are compared with those obtained with VMTK + Fluent, in which velocity conditions are prescribed at the inlets and a 50/50 mass split is prescribed

at the outlets (c). A slice through segment A1 of the left was examined in each case to match local Reynolds numbers and mass flow rates

Fig. 9.

Velocity magnitudes in three orthogonal slices of the aneurysm bulb were compared to test grid independence between coarse ($\Delta_{min} = 0.1$; left), medium ($\Delta_{min} = 0.05$; center), and fine ($\Delta_{min} = 0.025$; right) meshes: X-plane (a), Y-plane (b), and Z-plane (c)

Fig. 10.

Average wall shear stress (left) and surface pressure (right) were compared in the ACoA geometry to test grid independence between (a) coarse ($\Delta_{min} = 0.1$), (b) medium ($\Delta_{min} = 0.05$), and (c) fine ($\Delta_{min} = 0.025$) meshes

Fig. 11.

Streamlines, colored by pressure, illustrate fluid pathways through the ACoA aneurysm for each case; (a) the current approach and (b) the V-G-F case

Fig. 12.

Contours of surface pressure near the ACoA aneurysm bulb, computed using (a) the current method and (b) the V-G-F case

Fig. 13.

Contours of wall shear stress near the ACoA aneurysm bulb, computed using (a) the current method and (b) the V-G-F case. The contour range has been adjusted in each case to highlight similarities in shear stress distribution across the modeled surfaces

Fig. 14.

Comparison of velocity magnitudes in orthogonal slices through the center of the ACoA aneurysm bulb for the current method (left) and the V-G-F case (right): X-plane (a), Y-plane (b), and Z-plane (c)

Fig. 15.

The aneurysm bulb, highlighted in red, is delineated from its parent vessels by the ostium surface plane

Fig. 16.

A comparison of surface pressure (a) and wall shear stress (b) values calculated using the current approach (left) and the V-G-F approach (right)

Fig. 17.

A comparison of velocity magnitude in slices taken through the aneurysm in the direction parallel (b) and perpendicular (c) to the bulk flow, using the current approach (left) and the V-G-F approach (right). Slice locations are illustrated using the current case in (a)

Fig. 18.

A comparison of the segmentation aneurysm viewed from the top (a) and from the side (b) using the current approach (left) and the V-G-F approach (right)

Fig. 19.

Lack of resolution and a small gradient defining the vessel boundary allow for large variations in the segmentation results, as illustrated by sample y-plane slices (left) just upstream from the aneurysm (a) and through the aneurysm bulb (b). Contours of the current (black) and V-G-F (red) segmentation results are overlaid on each sample slice (right)

Characterization of CTA image quality for the flow phantom and the real intracranial aneurysms. Each image is separated into two regions – a bright region x_1 (object) with mean brightness intensity μ_1 , and a dark region x_2 (background) with mean brightness intensity μ_2 . The two regions are delineated by the segmentation contour, and include all segmented objects prior to tagging and removal. Image quality is measured in terms of contrast ratio μ_1/μ_2 , signal-to-noise ratio μ/σ in each region, and the overall contrast-to-noise ratio $|\mu_1 - \mu_2|/\sigma$.

Table 1

Image	μ_1	μ_2	μ_1/μ_2	μ/σ		$\frac{ \mu_1 - \mu_2 }{\sigma}$
				x_1	x_2	
Phantom	238.59	217.49	1.097	39.82	4.88	0.528
ACoA Aneurysm	130.38	66.44	1.962	1.95	1.16	0.937
MCA Aneurysm	138.96	35.57	3.91	7.45	2.43	5.39

Grid independence study. Average velocity magnitudes were compared in three orthogonal slices through the aneurysm bulb for the ACoA case. Error is calculated with respect to results obtained on the finest mesh.

Table 2

<i>min</i>	$\ u\ _{\text{average}}$			Error		
	X-plane	Y-plane	Z-plane	X-plane	Y-plane	Z-plane
0.1	0.2223	0.2245	0.2223	0.862%	0.582%	0.862%
0.05	0.2214	0.2236	0.2214	0.454%	0.179%	0.454%
0.025	0.2204	0.2232	0.2204	--	--	--

Table 3

Grid independence study. Average wall shear stress and surface pressure values were compared in the aneurysm bulb for the ACoA case. Error is calculated with respect to results obtained on the finest mesh.

<i>min</i>	WSS_{average}	Error	<i>P</i>_{average}	Error
0.1	1.719	14.272%	268.35	9.741%
0.05	2.009	1.132%	237.08	3.047%
0.025	2.032	--	244.53	--

Table 4

A comparison of three aneurysm indices in the current and V-G-F cases for both the ACoA and MCA aneurysms: Average wall shear stress in the bulb (WSS_{avg}), low shear area in the bulb (LSA), and the inflow concentration index (ICI).

Index	ACoA Aneurysm		MCA Aneurysm	
	Current Method	V-G-F Case	Current Method	V-G-F Case
WSS_{avg}	2.01 Pa	2.15 Pa	10.65 Pa	9.83 Pa
LSA	76.60%	76.55%	51.39%	43.25%
ICI	1.51	1.70	0.401	0.502