Computer-assisted extraction of intracranial aneurysms on 3D rotational angiograms for computational fluid dynamics modeling

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(Received 26 June 2009; revised 7 September 2009; accepted for publication 15 October 2009; published 13 November 2009)

Purpose: Three-dimensional rotational angiography (3DRA) is an evolving imaging procedure from traditional digital subtraction angiography and is gaining much interest for detecting intracranial aneurysms. Computational fluid dynamics (CFD) modeling plays an important role in understanding the biomechanical properties and in facilitating the prediction of aneurysm rupture. A successful computational study relies on an accurate description of the vascular geometry that is obtained from volumetric images.

Methods: The authors propose a new aneurysm segmentation algorithm to facilitate the study of CFD. This software combines a region-growing segmentation method with the 3D extension of a deformable contour based on a charged fluid model. A charged fluid model essentially consists of a set of charged elements that are governed by the nature of electrostatics. The approach requires no prior knowledge of anatomic structures and automatically segments the vasculature after the end-user selects a vessel section in a plane image.

Results: Experimental results on 15 cases indicate that aneurysm structures were effectively segmented and in good agreement with manual delineation outcomes. In comparison with the existing methods, the algorithm provided a much higher overlap index with respect to the ground truth. Furthermore, the outcomes of the proposed approach achieved a clean representation of vascular structures that is advantageous for hemodynamics analyses.

Conclusions: A new aneurysm segmentation framework in an attempt to automatically segment vascular structures in 3DRA image volumes has been developed. The proposed algorithm demonstrated promising performance and unique characteristics to adequately segment aneurysms in 3DRA image volumes for further study in computational fluid dynamics. © 2009 American Association of Physicists in Medicine. [DOI: [10.1118/1.3260841](https://doi.org/10.1118/1.3260841)]

Key words: aneurysms, 3DRA, segmentation, charged fluid model (CFM), computational fluid dynamics (CFD), conformity

I. INTRODUCTION

A cerebral aneurysm is an abnormal bulge or a diffuse dilation in the wall of a blood vessel that most commonly occurs in arteries at the base of the brain.¹ It is estimated that 4%–5% people in the United States will develop a brain aneurysm during their lifetime, about 20%–30% of them with multiple aneurysms. As an aneurysm develops, when the blood vessel becomes weakened, it begins to bulge out like a balloon. Often, the larger the balloon evolves, the greater the risk it may burst. For an aneurysm that has not bled, the risk of rupture appears to be related to its dimension and location.² Subarachnoid hemorrhage from a ruptured brain aneurysm can lead to a hemorrhagic stroke, which is the leading cause of mortality and morbidity worldwide.^{3–5}

Unfortunately, current technology cannot provide analo-

gous information *in vivo* through either invasive or noninvasive measurements in the initiation, growth, and rupture of cerebral aneurysms.⁶ Numerical simulations of computational fluid dynamics (CFD) have become a surrogate to achieve a better understanding of the brain aneurysm hemodynamics.^{5–8} Computational modeling can facilitate the investigation of intra-aneurysmal flow dynamics by providing useful biomechanics information to diagnosis and treatment planning. With recent advance in computational methods and modeling, simulation studies have been turned from idealized aneurysm geometries to realistic patient-based models.^{5,6,8} Patient-specific geometries of cerebral aneurysms are readily available in modern endovascular imaging modalities. Digital subtraction angiography (DSA), computed tomographic angiography (CTA), and magnetic reso-

nance angiography (MRA) have been the three most commonly used imaging techniques.^{9,10}

DSA has long been considered the gold standard for the detection of intracranial aneurysms.^{4,10–12} This technique uses fluoroscopy and iodine-based intravascular contrast material that is injected via a catheter into the femoral artery through the abdominal aorta and thoracic aorta, and into the carotid.¹² Consequently, it is treated as an invasive procedure that requires high skill to perform the study.^{4,13} DSA subtracts out images of anatomic structures other than blood vessels, e.g., bone, therefore making the blood vessels more distinguishable without interference of bony structures.¹⁴ With a high spatial resolution (0.15–0.3 mm) in a 1024×1024 matrix,^{4,11,13} DSA is still the most sensitive tool for the detection of cerebral aneurysms.^{14,15} However, its major limitations include the requirement of the operator with more experience and skill, and the necessity of repeated injections of contrast material and increased radiation dose to the patient.^{4,13,16} In addition, the limited number of projections may be a limitation in the evaluation of complicated vascular structures.¹⁷

In clinical practice, CTA has been the most frequently used noninvasive diagnostic technique for detection of intracranial aneurysms in the acute stage.^{11,18} Similar to DSA, CTA involves the use of ionizing radiation and iodine-based contrast material. Compared to DSA, however, the contrast material is injected into an antecubital vein instead of a femoral artery, CTA is associated with much less morbidity.¹² From the perspective of imaging, one major advantage of CTA is the generation of three-dimensional (3D) information on the geometries of intracranial arteries and cerebral aneurysms.^{11,15} Typical CTA protocols involve a 512×512 matrix with 0.23–0.45 mm pixel size and 0.5–1.3 mm slice thickness.^{4,10,14,15,18} Nevertheless, CTA may lack visibility of small arteries and have difficulty in differentiating the infundibular dilation at the origin of an artery from an aneurysm.^{14,15} Other potential limitations to CTA include lower resolution, interpolation errors, inability to identify thrombosis and calcification, close intensity distributions for bones and vessels, and the need for optimized contrast gradient-injection timing.^{4,8}

Alternatively, time-of-flight MRA does not utilize ionizing radiation or iodinated contrast material while providing 3D anatomic images of cerebral blood vessels.^{4,10,19} While the bone does not disturb the images when compared to CTA, there is no radiation exposure and no administration of contrast material in this noninvasive procedure.^{10,20} However, compared to DSA and CTA, MRA has a lower spatial resolution of a 256×256 matrix with pixel size 0.78–1.25 mm and slice thickness 0.7–1.6 mm,^{11,18–20} which results in lower detection sensitivity for smaller aneurysms.^{4,15} The sensitivity for detection of intracranial aneurysms smaller than 3 mm was extremely poor with approximately 38% and 61% for MRA and CTA, respectively.²¹ MRA also requires comparatively long imaging times that frequently lead to patient motion artifacts and degradation of image quality.^{4,11} In addition, MRA may underestimate the size of intracranial

aneurysms and may not completely display the entire geometry of an aneurysm due to signal loss in situations of low or complex flows.^{8,12}

Recently, there has been increasing interest in utilizing 3D rotational angiography (3DRA) for the detection and diagnosis of intracranial aneurysms.^{16,18,22} In comparison with DSA, 3DRA provides relative operator independency with a more confident choice of embolization techniques and materials,^{13,16} uses lower radiation dose and less contrast material to the patient,¹⁶ and depicts much smaller (≤ 3 mm) additional aneurysms.¹³ Compared to CTA and MRA, 3DRA provides higher spatial resolution (128^3 – 512^3 , with voxel size of 0.42–1 mm) (Refs. 8, 13, and 23) and lower sensitivity to technical factors, e.g., patient motion.⁸ It has been demonstrated that CTA is more accurate than MRA and 3DRA is more accurate than CTA.¹⁸ Moreover, 3DRA offers greater ease of reconstruction and is more appropriate for volumetric assessment of intracranial aneurysms.^{8,18}

To conduct a successful numerical simulation, the region around the aneurysm has to be isolated from the rest of the vascular tree in volumetric angiograms.⁵ Previous studies have shown that the geometry played the most crucial role in obtaining accurate intra-aneurysmal hemodynamic properties.^{5,6,24} To achieve precise evaluation of cerebral aneurysm hemodynamics studies, a number of approaches have been proposed to extract aneurysms associated with surrounding vessels. Gray-level thresholding (GLT) with certain degrees of manual intervention has been widely used by many researchers^{5,15,18} due to its simplicity. Thresholding is extremely computationally efficient and fast, which can be easily executed in real time. However, the “ideal” threshold to depict intracranial vessels has to be found interactively and depends on many parameters. Castro *et al.*⁸ used a seeded region-growing (SRG) algorithm to segment cerebral vessels with parameters selected by trial and error. Using SRG alone, there may be undesired holes inside the segmented vessels, leading to poor results for CFD analysis. Boskamp *et al.*²⁴ and Arimura *et al.*²⁵ proposed the use of SRG associated with GLT for the segmentation of vascular structures. For a successful application of this approach, it is critical to choose appropriate parameter values. Indeed, all the described methods could not directly provide segmentation results with isolated aneurysm structures for CFD study and no integrated commercially available software packages seem to satisfy such demands.

In this article, an attempt was made to try to investigate the use of a 3D deformable model associated with SRG to automatically extract clean cerebral aneurysms in volumetric images for CFD modeling. In our approach, a SRG method was used as a precursor to segment a vessel section in a 2D image, from which the initial point for the subsequent procedure was obtained. A constraint cube was then generated to enclose and isolate part of 3D vascular structures from original 3DRA images. A 3D deformable contour extended from the charged fluid model²⁶ was applied to extract the vascular structure in the constraint cube. After the evolution was terminated in that cube, a detection procedure was performed to

FIG. 1. Illustration of the smallest deformable contours using the charged fluid model. Four elements with the grid spacing equal to h constitute the minimum interface in 2D (left) and eight in 3D (right).

label the intersections of the vessel and cube surfaces. The subsequent cubes located at the centers of the intersections were generated to enclose the 3D deformable contour for further evolution, if any. The generation of the cube toward next positions was repeated until no intersection was detected. This new technique is called the charged fluid-based aneurysm segmentation (CFAS) algorithm.

II. CHARGED FLUID MODEL

A charged fluid model²⁶ is essentially a set of invisible elements describing a deformable contour whose characteristics are governed by the nature of electrostatics. Each of these elements carries a charge with the same sign and constitutes a propagating interface that is modeled as the surface of an isolated conductor. As illustrated in Fig. 1, to enable correct and uniform evolution in a free space, the numbers of elements to constitute a minimum interface are four and eight in 2D and 3D, respectively. Accordingly, the fluid elements repel each other due to the electric forces and advance toward an equilibrium state in such a way that the electrostatic energy is minimized. When electrostatic equilibrium is achieved, the electric force at each fluid element is perpendicular to the contour and has a magnitude proportional to the charge of the corresponding element. It is this electric force that is used to guide the evolution of the deformable contour. In essence, the electrostatic system in the deformable contour is governed by Poisson's equation,

$$\nabla^2 \Phi = -4\pi\rho, \quad (1)$$

where Φ and ρ are the electric potential and charge density of the system, respectively. Optimized numerical techniques are used to efficiently solve Eq. (1) based on the finite-size particle method associated with the fast Fourier transform algorithm.

To interact with the image data, the fluid elements deform in response to the change in gray-level intensity, i.e., the image gradient. More precisely, the charged fluid model can be expressed as

$$\Psi^{n+1} = \Psi^n + (\vec{E}_{\text{ele}} + \beta \vec{E}_{\text{img}}) \cdot \nabla \Psi \cdot \Delta t, \quad (2)$$

where Ψ represents the evolving curve in 2D or surface in 3D, n is a time index, β is a weight for balancing, and Δt is the time step. In Eq. (2), $\vec{E}_{\text{ele}}$ is the electric field in electrostatic equilibrium

FIG. 2. Flowchart of the automatic aneurysm segmentation framework CFAS on 3DRA image volumes.

$$\vec{E}_{\text{ele}} = -\nabla \Phi, \quad (3)$$

where Φ is the equilibrium potential from Eq. (1) and $\vec{E}_{\text{img}}$ is the image field derived from the image gradient

$$\vec{E}_{\text{img}} = \nabla G_{\sigma} * I, \quad (4)$$

where G_{σ} is a Gaussian filter with standard deviation σ , I is the input image data, and $*$ represents convolution. When the magnitude of the image field is insignificant, i.e., in a relatively homogenous region, the contour of the charged fluid model deforms approximately in its normal direction based

FIG. 3. The main application window after loading image data, which is mainly divided into a functional toolbar (top), a control panel for specific processing adjustments (left), and a viewing area (right). The viewing area shows the segmentation of the cross section of a vessel after applying the SRG and the computation of the center of mass and its bounds.

on the electric field. However, when the image gradient is stronger than the electric field, the fluid element changes its advancement direction dramatically and may be confined at the corresponding position. The charged fluid model relies on salient image gradient forces to accommodate the evolving directions of the fluid elements so that the contour can be stopped at boundaries of interest.

FIG. 4. Schematically illustrating the generation of an initial constraint cube located at the center of mass of the segmented vessel in 2D (left). A 3D charged fluid model is then applied to segment the 3D vascular structure in that constraint cube. After the segmentation is terminated, a detection procedure is applied to label the intersections of the vessel and cube surfaces. The subsequent cubes located at the centers of the intersections were generated to enclose the 3D deformable contour for further evolution (right).

FIG. 5. Illustration of the evolution of the 3D charged fluid model in a constraint cube in segmenting the vessel with a bifurcation structure, from top left to bottom right.

Conceptually, the charged fluid behaves like a liquid such that it flows through and around different objects and noise in an image. It has been shown that the charged fluid model performed better than level set based geometric deformable models in segmenting anatomic structures with blurred boundaries and large intensity variations in noisy images.²⁶ In addition, it requires no velocity and acceleration computation, and no direct curvature and normal direction calculation for advancing the contour. The topological change in the propagating interface is handled automatically and the charged fluid model provides segmentation results with sub-pixel precision. From the perspective of practical use, this algorithm needs only one effective parameter and requires no prior knowledge of anatomic structures. In this study, we have extended the charged fluid model to a 3D segmentation algorithm for achieving a higher degree of automation, which is further incorporated into our aneurysm segmentation framework.

III. ANEURYSM SEGMENTATION FRAMEWORK

The proposed aneurysm segmentation framework, CFAS, aims to be a convenient resource for radiologists, physicists, and other radiologic scientists working on aneurysm related research. The outline of the overall aneurysm segmentation is depicted in Fig. 2. First, a user friendly interface is used to load 3DRA image data with a number of useful manipulation tools. As shown in Fig. 3, the software was developed in JAVA for its robust abilities running on various operating systems across multiple platforms, e.g., Windows, Mac, Linux, and Unix. An image scrolling tool is then provided to help the end-user choose an appropriate vessel section in a 2D image to start the automatic extraction process. An SRG algorithm is applied to segment the selected vessel section and its size is subsequently estimated by the system. In our approach, the growing process starts from the mouse click point by adding in adjacent pixels that satisfy specified homogeneity criteria. If the homogeneity criteria are omitted,

FIG. 6. Evolution of the vessel segmentation in an internal carotid artery using the CFAS framework.

the vessel section will be poorly segmented, leading to failure of subsequent procedures. After the growing process is completed, the system computes the center of mass and bounds of the segmented 2D vessel, as illustrated in Fig. 3. Doing this allows the system to automatically provide an initial point and to estimate the size of the vessel for the following iterative procedures.

A constraint cube located at the center of mass with a dimension approximately three times larger than the vessel size is generated to enclose and isolate part of vascular structures from the volumetric images for the 3D segmentation process, as illustrated in Fig. 4. This setting of the cube dimension strikes a compromise between computation cost and segmentation accuracy. A 3D Gaussian filter is then applied

FIG. 7. Comparison of different methods in segmenting an internal carotid artery aneurysm. (a) In GLT, there were unconnected components, (b) SRG included undesired vessels, and (c) CFAS provided a clean representation.

FIG. 8. Segmentation of a posterior communicating artery aneurysm using the SRG method. Part of the vessel (indicated by the arrow) was broken due to incomplete segmentation.

to smooth the cropped image volumes, followed by the 3D charged fluid model initialized inside the vessel. As illustrated in Fig. 5, the charged fluid evolves toward the boundaries of the vessel and is constrained by the cube surfaces until the extraction of the vascular structure is completed. Subsequently, a detection procedure is applied to label the intersections of the segmented vessel and cube surfaces. The next constraint cubes are located at the centers of the intersections and generated to isolate the vessel segments from the original images, as shown in Fig. 4. If any next constraint cube is reachable, the procedure goes back to the segmentation step and repeats the subsequent processes until no further cube is required for segmenting the vessel. Finally, the system outputs the extracted aneurysm associated with surrounding vessels for further analysis in CFD modeling. One particular characteristic of the CFAS framework is that tiny vessels with diameters approximately smaller than $3 \sim 4$ voxels were excluded from the segmentation results when the grid spacing $h=1$ (see Fig. 1). Figure 6 shows a typical example for the evolution of vascular segmentation based on the proposed segmentation framework in an internal carotid artery.

IV. RESULTS

To assess the capabilities of our aneurysm segmentation algorithm, CFAS, we have successfully applied it to segment 15 vascular structures in 3DRA image volumes. The image data were acquired from the medical image database in the Division of Interventional Neuro Radiology, Department of Radiology, UCLA, Los Angeles, CA, under an approved human research subject protection protocol. The size of these images was $256 \times 256 \times 256$ with spatial resolution of $1 \times 1 \times 1 \text{ mm}^3$ and the raw data of the images were directly used to examine our algorithm after convolving with a 3D $3 \times 3 \times 3$ Gaussian filter. Larger sizes of filters, say $5 \times 5 \times 5$, should be avoided because they may blur and shift the real boundary position during the convolution. In this study, the grid spacing h was set to 1 voxel. For visualization, the dynamic range of the images was compressed into 256 gray levels. All experiments were executed on a modern computer with an Intel CPU 2.33 GHz running a Linux operating system. The results were quantitatively evaluated using the conformity coefficient²⁷

$$\text{Conformity} = \left(1 - \frac{\Theta_{\text{FP}} + \Theta_{\text{FN}}}{\Theta_{\text{TP}}} \right) \times 100\%, \quad (5)$$

where Θ_{FP} represents false positives of the segmentation results with respect to the ground truth, Θ_{FN} represents false negatives, and Θ_{TP} represents true positives.

Figure 7 presents the extraction results of an internal carotid artery aneurysm using the GLT, SRG, and CFAS algorithms. Although both GLT and SRG methods produced approximately the entire vascular tree with tiny vessels, there were many undesired structures that could disturb the diagnoses of the aneurysm. On the other hand, the CFAS algorithm offered a clean representation of the aneurysm with necessary surrounding vessels for the CFD analyses. Having many displeasing segments in and around the vasculature, the aneurysm segmented using both GLT and SRG methods were somewhat not easy to be detected. Furthermore, Fig. 8 shows the segmentation result of a posterior communicating artery aneurysm using the SRG method. Note that a part of the vessel just above the aneurysm was broken due to incomplete segmentation. This illustrates one of the disadvantages

FIG. 9. Illustration of internal holes (the white regions indicated by the arrows) in the segmented vascular images using the SRG method. (a) Anterior cerebral artery. (b) and (c) Internal carotid artery structures. (d) Aneurysm with coils.

FIG. 10. Aneurysm segmentation results using the CFAS algorithm (left) in comparison with the MIP images (right). (a) Basilar artery aneurysm. (b) Carotid-ophthalmic aneurysm. (c) Middle cerebral artery aneurysm. (d) Posterior communicating artery aneurysm. (e) Intracranial artery aneurysm with coils.

of the SRG algorithm in that there were holes inside the segmented vessels, as shown in Fig. 9. Owing to large gray-level variations along and across the vessels, the holes were inevitably produced using this technique. Such interior holes in the segmented vessels could result in failure for CFD analyses. In contrast, the CFAS framework provided an automatic scheme to acquire clean aneurysm structures for further studies in CFD.

A variety of aneurysm structures were segmented using the proposed CFAS algorithm and in comparison with the corresponding maximum intensity projection (MIP) images. The MIP was obtained in that the stack of slices was collapsed into a single image for visualization by projecting through the stack that assigned to each pixel in the projection

FIG. 11. Analyses of the segmentation of an internal carotid aneurysm in 3DRA images. (a) Segmentation results obtained using the CFAS framework. (b) Manual delineation results of the original data locally magnified. (c) Another view of the extraction results. (d) The corresponding view of the MIP image.

the maximum intensity over all slices. A basilar artery aneurysm with five connecting vessels was effectively extracted from the 3DRA image volume and in good accordance with the MIP image, as shown in Fig. 10(a). We show in Fig. 10(b) the segmentation of a carotid-ophthalmic aneurysm and its MIP image. Note that in the MIP image, there were considerable amounts of variation in intensity along the vessel path, which had no influence on the segmentation of this vascular structure using our CFAS algorithm.

We also applied this new technique to segment a convoluted middle cerebral artery aneurysm, as illustrated in Fig. 10(c). Although the vascular structure was with blurred boundaries and nonuniform intensity distributions along the vessel centerline, the extraction result was in agreement with the MIP image. In Fig. 10(d), we present the segmentation of an aneurysm structure in a posterior communicating artery. Once again there were severely nonuniform intensity distributions along the convoluted vessel centerline as shown in the MIP image. Due to the embedded scheme of constraint cube extraction, the CFAS algorithm continued to successfully extract the aneurysm structure while overcoming the inevitable inhomogeneity in the 3DRA image data. The ability of segmenting an intracranial artery aneurysm embolized with coils was evaluated, as depicted in Fig. 10(e). As shown in the MIP image, the aneurysm had relatively bright and extremely inhomogeneous intensity distributions due to the coils, whose purpose is to promote blood coagulation and thus hamper its rupture. The extraction result was somewhat influenced by this severe inhomogeneity so that part of connecting vessels was missing.

In Fig. 11, we show a qualitative comparison between the segmented internal carotid artery aneurysm structure and the manual delineation outcome, which was obtained using slice-by-slice delineation of vessels by experts in a

FIG. 12. Evaluation of the aneurysm segmentation results using the CFAS algorithm in various vascular structures. The interior solid regions represent the segmented vessels in 2D images, which had approximately one to three pixel differences between the extracted boundaries and the manual delineated contours.

$256 \times 231 \times 256$ image volume of the original data locally magnified. These manual delineation masks, which are the best expected result, are often used as ground truth for evaluation.²⁷ Obviously, a good agreement between the automatic segmentation and the ground truth was achieved. The extraction result was also in accordance with the MIP image, as shown in Figs. 11(c) and 11(d). To quantitatively evaluate our CFAS algorithm, we measured the distances between the segmented boundaries and the manual delineated contours. The distances were found to be approximately in the range of one to three pixels, as illustrated in Fig. 12. We present in Fig. 13 the conformity values for the 15 segmentations in this study using different methods. While both GLT and SRG methods had low conformity average scores of 30.54% and 35.17%, respectively, the CFAS algorithm achieved a much higher average of 68.36%. Lastly, the computation times were case dependent with an average of 6 min approximately, as summarized in Table I.

V. DISCUSSION

We have developed a new aneurysm segmentation algorithm, CFAS, which combined an SRG segmentation method with a 3D charged fluid model to automatically extract vascular structures in volumetric images. The unique properties and essential characteristics of this computer-assisted tool with minimal user intervention were demonstrated in extracting a variety of aneurysm structures in 3DRA image volumes without requiring prior knowledge of the underlying anatomy. Good agreements between the extraction results

and the MIP images as well as manual delineation outcomes were achieved. We also compared our results to the outcomes obtained using the GLT and SRG methods. Quantitative analyses indicated that the CFAS algorithm provided a much higher conformity score (68.36%) than these two approaches (30.54% and 35.17%). In particular, both GLT and SRG methods produced quite sophisticated vascular structures with undesired holes inside the segmented vessels and unconnected vessel segments, which could disturb the diagnoses and analyses of aneurysms. It also required laborious user intervention to select appropriate parameters for each individual case as compared to our CFAS algorithm.

In this study, it is noted that the branches of the segmented vascular structures were terminated at the vicinities of small vessels, which are approximately 3~4 voxels. This is because the grid spacing h was set to 1 voxel and the allowed dimension for the smallest deformable surface was equal to 8 voxels in all experiments executed. As a consequence of this intrinsic characteristic, the deformable surface stopped at the vicinities of vessels with narrow diameters. It is often desired to isolate the target aneurysm from the rest of the arterial network for CFD modeling.⁵ Such a clean representation of vasculature is somewhat beneficial to radiologists, neurosurgeons, and researchers in brain hemodynamics analysis without the influence of trivial vessels. Nevertheless, different levels of vascular structures could be obtained through multiscale analysis using a number of grid spacing

TABLE I. List of the computation times associated with the number of cases being processed.

Time (min)	No. of case
(0,1]	2
(1,2]	3
(2,4]	4
(4,8]	2
(8,16]	3
(16,24]	1

FIG. 13. Conformity scores for the methods evaluated in this study. While both GLT and SRG methods had large variations with low averages of 30.54% and 35.17%, respectively, the CFAS algorithm achieved a much higher average of 68.36%.

FIG. 14. Segmentation results of a posterior communicating artery aneurysm using different values of the grid spacing h . (a) $h=1$. (b) $h=0.5$.

values from coarse to dense. As illustrated in Fig. 14, the segmentation result of a posterior communicating artery aneurysm using $h=0.5$ revealed more detail of the vasculature as compared to the result of using $h=1$.

In summary, this new algorithm, CFAS, demonstrated promising performance in its capabilities to successfully segment aneurysm structures in 3DRA image volumes, which was intensively evaluated both qualitatively and quantitatively. Due to the generality of the proposed framework, it could be applied to the segmentation of other anatomic structures and medical imaging modalities such as MRA and CTA. Although no prior knowledge of anatomy is required, it would be advantageous to incorporate anatomic knowledge into the segmentation framework to better identify the boundary of interest, particularly when the boundary is extremely unclear or blurred. Further study is required to improve the accuracy of the vessel segmentation in some situations with complex geometry and severe intensity variation.

ACKNOWLEDGMENTS

This work was supported in part by the NIH/NIMH research Grant No. U54 RR021813 entitled Center for Computational Biology (CCB) and the National Science Council under Research Grant Nos. NSC96-2811-E-010-001 and NSC97-2811-B-010-028. Additional support was provided by the Ministry of Education, aim for the Top University Plan, through the National Science Council under Research Grant Nos. NSC97-2627-B-010-005 and NSC97-3114-E-010-002.

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