3-D Deformable Model Segmentation of Abdominal Aortic Aneurysm

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ABSTRACT

In this paper we propose a technique for 3-D segmentation of abdominal aortic aneurysm (AAA) from computed tomography angiography (CTA) images. Output data (3-D model) form the proposed method can be used for measurement of aortic shape and dimensions. Knowledge of aortic shape and size is very important in planning of minimally invasive procedure that is for selection of appropriate stent graft device for treatment of AAA. The technique is based on a 3-D deformable model and utilizes the level-set algorithm for implementation of the method. The method performs 3-D segmentation of CTA images and extracts a 3-D model of aortic wall. Once the 3-D model of aortic wall is available it is easy to perform all required measurements for appropriate stent graft selection. The method proposed in this paper uses the level-set algorithm for deformable models, instead of the classical snake algorithm. The main advantage of the level set algorithm is that it enables easy segmentation of complex structures, surpassing most of the drawbacks of the classical approach. We have extended the deformable model to incorporate the a priori knowledge about the shape of the AAA. This helps direct the evolution of the deformable model to correctly segment the aorta. The algorithm has been implemented in IDL and C languages. Experiments have been performed using real patient CTA images and have shown good results.

Keywords: abdominal aortic aneurysm, deformable models, level set, image analysis, image segmentation

1. INTRODUCTION

Abdominal aortic aneurysm (AAA) [1], [2], [11], [12] represents a vascular disease, which affects about 2% of people older than 65 years. Such AAAs are caused by degenerative, inflammatory, mycotic diseases as well as by arteriosclerosis. 50% of AAAs are detected by chance [11]. In up to 9% of those patients the AAA will rupture. As a fatal consequence 70 - 90% of patients with ruptured AAA will die [12]. Although AAA can be imaged by plain abdominal films, ultrasound, computed tomography, magnetic resonance tomography the gold standard is represented by intraarterial digital subtraction angiography.

Today many treatment options exist. Open surgery has obvious disadvantage because of its invasive nature. For this reason, an alternative procedure has been proposed recently that is based on endovascular placement of aortic stent graft through a minimally invasive opening on the patient body. However, this method requires prior knowledge of aortic shape and measurements in order to choose the stent graft device of appropriate shape and size. This means that accurate segmentation and measurements of AAA must be made prior to the surgical procedure.

A number of different modalities have been used for imaging of AAA, such as ultrasound, digital subtraction angiography (DSA), computed tomography angiography (CTA), and contrast-agent enhanced MR angiography [3].]. Modern medical imaging techniques followed by appropriate image analysis methods [4] have shown to be useful for measurements of AAA [5], [6].

In this paper, we describe a 3-D image analysis technique for segmentation of AAA from CTA images. The technique is based on 3-D deformable model and utilizes a level-set algorithm for implementation of the method. The method performs 3-D segmentation of CT images and extracts a 3-D model of aortic wall. Having available such 3-D model of aortic wall, all measurements required for appropriate stent graft selection can be easily performed.

In our previous work [6], we have developed a semi automatic 3-D technique for aneurysm segmentation that is based on 2-D active contours with additional forces introduced for 3-D interaction between the slices. The method uses the classical 2-D active contour algorithm developed by Kass et al. [7]. The method proposed in this paper uses the level-set algorithm [10] instead of the classical active contour algorithm. To segment outer aortic wall some adaptations to the basic level-set algorithm have to be made due to specific problems encountered in this problem. In our previous work [11], we have suggested an additional stopping criterion for level-set algorithm to solve such problems. The adaptation of level-set algorithm proposed in this paper involves tracking of deformable model expansion.

2. LEVEL-SET METHOD FOR DEFORMABLE MODEL-BASED SEGMENTATION

Deformable models have shown to be a powerful tool for medical image segmentation [8]. The original 2-D active contour algorithm as described by Kass et al. [7] uses active contours (snakes) and is widely used. The classical snake approach has several disadvantages: (i) difficulties with segmentation of topologically complex structures, and (ii) complex implementation in 3-D. To overcome these difficulties, several modifications to the original active contour have been proposed. One of modifications is the level-set method [9], [10] which we utilize in our approach. In this section, we will give a short description of level-set method in 2-D segmentation. Extension to three-dimensional case, which we use in our work, is straightforward.

In this approach for shape modeling, a 2-D curve γ is represented by a 3-D function Ψ (Figure 1.).

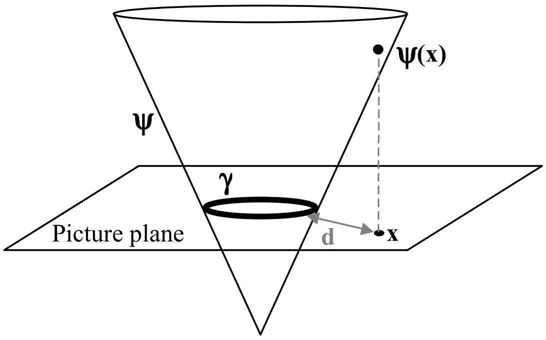

Figure 1. Level set function Ψ

Ψ is built on Equation 1 and is chosen to be the distance function of the 2-D curve γ

$$\Psi(x, t = 0) = \pm d \tag{1}$$

where $x \in \mathbf{R}^2$ are points in image space. The sign in Equation 1 determines whether the point lies outside or inside the 2-D curve $\gamma(t=0)$. In this manner, γ is represented by the zero level set $\gamma(t) = \{x \in \mathbf{R}^2 \mid \Psi(x, t)=0\}$ of the level set function Ψ. The level set method then evolves the 3-D function Ψ instead of the original 2-D curve. The motion of 3-D function Ψ is described by means of a partial differential equation (PDE) shown in Equation 2.

Using such an approach we are evolving a surface instead of evolving a curve, which makes the approach more complex, but the level-set method introduces some new qualities and resolves some difficulties encountered with the classical snake method. An important advantage of the level-set method is that as long as the surface stays smooth, its zero level set can take any shape, change topology, brake and merge. Another advantage is that it is easy to build accurate numerical schemes to approximate the equations of motion.

The evolution PDE for evolution of the function $\Psi(x,t)$ has the following form:

$$\frac{\partial \Psi(x,t)}{\partial t} + F\left|\nabla \Psi\right| = 0 \tag{2}$$

with a given initial condition $\Psi(x, t=0)$. For numerical solution of the Equation 2 it is necessary to perform discretization in both space and time domains. For this purpose we discretize space coordinates using a uniform mesh of spacing h, with grid nodes denoted by indices ij. Let Ψ_{ij}^{n} be the approximation to the solution $\Psi(ih, jh, n\Delta t)$, where Δt is the time step. The expression for Ψ_{ij}^{n+1} can be derived using the upwind finite difference method, which gives us the final iteration expression in Equation 3.

$$\Psi_{ij}^{n+1} = \Psi_{ij}^{n} - \Delta t F \left| \nabla_{ij} \Psi_{ij}^{n} \right| \tag{3}$$

The speed term F depends on the curvature K and is separated into a constant advection term F_0 and the remainder $F_1(K)$, that is

$$F(K) = F_0 + F_1(K) \tag{4}$$

The advection term F_0 defines a uniform direction speed of the front, which corresponds to inflation force in classical snake models. The diffusion term $F_1(K)$ depends on the local curvature and smoothes out regions of high curvature thus corresponding to internal force in classical snake models. We use the following expression for the speed term

$$F = 1 - \varepsilon K \tag{5}$$

where ε is the entropy condition, which regulates the smoothness of the curve.

The curvature is obtained from the divergence of the gradient of the unit normal vector to front, that is

$$K = \nabla \frac{\nabla \Psi}{\left|\nabla \Psi\right|} = \frac{\Psi_{xx}\Psi_y^2 - 2\Psi_x\Psi_y\Psi_{xy} + \Psi_{yy}\Psi_x^2}{(\Psi_x^2 + \Psi_y^2)^{3/2}} \tag{6}$$

In order to segment images an image based condition has to be included in the speed function F. This image based condition would cause propagating front to stop at desired object boundary. Multiplying the speed function F with a quantity k provides the needed image influence. The term k is based on the image gradient since gradient provides information about edges and object borders. The term k can be defined in several ways and we use the following form.

$$k(x, y) = e^{-\left|\nabla G_\sigma * I(x,y)\right|} \tag{7}$$

where $G_\sigma * I$ denotes image convolved with Gaussian smoothing filter whose characteristic width is σ. This Gaussian low pass filter removes some noise from image thus eliminating possible problems induced by noise.

We use the narrow band extension to level-set algorithm, as proposed by Sethian et al. [10] where the function Ψ is evolved by updating the level-set function only at a small set of points in the neighborhood of zero level-set called the narrow band. The narrow band is δ pixels wide. During one time step the value of Ψ outside the narrow band is stationary and zero level-set cannot move past the narrow band. After a given number of iterations the curve γ, the level-set function, and the new narrow band are recalculated and the process is repeated. This extension allows us to run calculations only inside narrow band thus reducing overall computing time. Another advantage is that, for each point of Ψ we can use its own curvature K instead of curvature of the nearest zero level-set point. Originally, curvature of the closest zero level-set point should be used for each Ψ point, but inside the narrow band we can approximate curvature of the zero level-set with points own curvature.

In the above text, we have described the level set method for segmenting two-dimensional images. Extension to three dimensions is straightforward by extending the array structures and gradient operators. In that case, Ψ is a 4-D surface and the algorithm is adapted to 3-D. Expression for curvature calculation of the level set function in 3-D case is stated in [9].

$$K = \frac{\Psi_{xx}(\Psi_y^2 + \Psi_z^2) + \Psi_{yy}(\Psi_x^2 + \Psi_z^2) + \Psi_{zz}(\Psi_x^2 + \Psi_y^2) - 2\Psi_x\Psi_y\Psi_{xy} - 2\Psi_x\Psi_z\Psi_{xz} - 2\Psi_z\Psi_y\Psi_{zy}}{(\Psi_x^2 + \Psi_y^2 + \Psi_z^2)^{3/2}} \tag{8}$$

3. 3-D ABDOMINAL AORTIC ANEURYSM SEGMENTATION

We apply the level-set method to the problem of AAA segmentation. The input to the level-set algorithm in our case is a 3-D array of volumetric CTA data of the human abdomen. As a pre-processing step, a manual extraction of the region of interest containing the AAA from the volumetric data is performed. This step reduces memory requirements and decreases algorithms execution time.

The segmentation is performed in two steps. The inner boundary of aorta (perfused volume) is segmented in the first step using a 3-D deformable balloon. This step requires manual initialization of deformable model. The outer boundary of aorta is segmented in the second step where segmented inner boundary is used for the initial contours. This step utilizes 2-D modified level-set algorithm.

For segmentation of the inner aortic boundary, we use the basic 3D level-set algorithm described in the previous section. In order to use level-set deformable model, an initial surface has to be defined. We choose the initial surface γ_{init1} to be a sphere because of its simplicity. The sphere center and radius have to be defined manually by the user so that the sphere resides entirely inside the abdominal aorta. The algorithm then evolves the surface γ until it stops changing. The outline of the algorithm is shown in Table 1.

Create initial surface γ_{init1} and initial Ψ_1
repeat
    for i =1,...,N_{iter1} **do**
        Execute iteration in Equation 4
    end for
    Recalculate surface γ_1
    Recalculate narrow band
    Reinitiate Ψ_1 in narrow band
until γ_1 stops changing

Table.1. The level set algorithm for abdominal aortic aneurysm segmentation.

The output of the algorithm is the final surface γ_{end1} representing the internal boundary of the aorta. The final γ_{end1} from this step is also used to produce initial conditions in the second step: calculation of outer aortic boundaries.

The implementation of level-set deformable model for 3-D segmentation of inner aortic boundaries is straightforward because of good image conditions, that is the high contrast between aortic interior and aortic wall. This is due to angiography technique used in CT data acquisition. This however is not the case while segmenting outer aorta boundary. The main difficulty comes from the fact that surrounding tissue has the same optical density as aortic wall and on several places, they are very close together, making it impossible to determine border between them. The level-set algorithm can successfully deal with small boundary gaps thanks to its local curvature based speed term, but cannot stop propagation of its zero level-set inside surrounding tissue where the boundary gap is large. This and variations in aortic diameter along aorta, especially in aneurysm area, led us to introduce some modifications to the 2-D level-set algorithm.

The enhancement to level-set algorithm we introduced tracking of curve expansion. This modification stops a segment of the evolving curve when its length expands past predefined percentage. That way, the deformable model won't be able to penetrate into surrounding tissue. Since the level-set algorithm has a nice property that it is not necessary to track movement of each point the level-set algorithm has to be adopted to provide curve segment tracking.

The evolving contour can be divided into moving segments, which are delimited by contour points that have already been stopped by the stopping criterion. Expansion of each of those segments must be traced separately. There is also possibility that two segments will merge so a merging of expansion coefficients has also had to be implemented. Expansion coefficient is defined by the iterative expression in the Equation 9

$$X_{n+1} = X_n \frac{N_{n+1} + S_{n+1}}{N_n} \tag{9}$$

where N_n represents number of moving points in contour segment in given time step n and S_n represents the number of new static points in the current segment in the current time step n. The expansion coefficient of the initial contour equals one.

When the evolving curve is growing the expansion coefficient X is also growing and we stop evolution of the curve segment when X reaches predefined level. This predefined level has to be determined experimentally for each application and it depends on ratio of ending curve length and initial curve length. This stopping criterion, by itself, could prematurely stop evolving contour even inside aorta. Since this is not desired behavior, another criterion has been introduced. Only those segments are stooped whose expansion coefficient is larger than predefined value and moving point ratio R (Equation 10.) is greater then predefined level.

$$R_{n+1} = \frac{N_{n+1}}{N_n} \tag{10}$$

The moving point ratio is used to distinguish the case when we want the expansion coefficient to act as the stopping criterion and the case when we do not want that. The expansion coefficient stopping criterion will not be applied if the moving points ratio is less then predefined value (usually set to 1), which is the case when the contour is approaching to the closed border. This basically means that the moving part of contour segment is shrinking. Moving point ratio that is greater than this predefined value is typical for contour leaking past the outer aortic wall when evolving contour starts filling surrounding tissue.

The initial curve γ_{init2} for the 2-D level-set deformable model is chosen to be the inner aortic boundary segmented in previous step.

In outer aortic boundary segmentation we use thresholded CT images for image gradient computation (Figure 1d), 2d)) ,in order to eliminate inner aortic boundaries interference. Since this algorithm can also be used for post procedure evaluation, the influence of stent graft on image gradient is also eliminated this way. To stop propagation of deformable model into surrounding tissue the speed function coefficients are modified to increase curvature influence. The modified algorithm shown in Table 2. is run to segment outer aortic boundary.

repeat for all slices
    Calculate initial curve γ_{init2} and initial Ψ_2
    repeat
        for i =1,...,N_{iter2} **do**
            Execute iteration in Equation 4
        end for
        Recalculate curve γ_2
        Recalculate narrow band
        Reinitiate Ψ_2 in narrow band
        if $p_{exp} > p_0$ **then**
            Stop segment evolution
    until γ stops changing

Table.2. The level set algorithm for abdominal aortic aneurysm segmentation.

After performing both steps in aortic segmentation we end up with 3-D model of abdominal aorta, on which measurements can be performed.

The major part of the algorithm has been implemented in IDL development environment while the most computationally complex steps have been implemented in C programming language.

4. RESULTS AND DISCUSSION

The algorithm has been tested using CT angiography images of a real patient. Segmentation has been performed on a manually pre-selected volume. Figures 1 and 2 show the results of segmentation using the proposed algorithm. Subfigures a) show a slice of input data, subfigures b) show gradient image used for inner aortic border segmentation, subfigures c) show segmented inner aortic border over the original slice and subfigures d) show gradient of thresholded image used for outer aortic border and segmented outer aortic borders are shown in subfigures e). It can be observed on the resulting images that inner aortic border segmentation (subfigure c) is satisfying. In segmentation of outer aortic border (subfigure e) in problematic areas with large boundary gaps (subfigures d) that algorithm stops deformable model where it should even though there is no image gradient. A closer look at segmentation results of outer aortic border reveals that on large boundary gaps deformable model has actually slightly entered surrounding tissue. Since physicians desire high accuracy of segmentation and the resulting model of aorta such small inaccuracies pose problem so further accuracy improvement is our next research step.

5. CONCLUSION

Stent graft placement has been recently introduced as a method for less invasive treatment of abdominal aortic aneurysm. This procedure requires prior knowledge of aortic dimensions, especially in the aneurysm area, so accurate measurements of the aneurysm area for selection of appropriate stent graft shape and size. These measurements are performed by imaging the patient using various medical imaging modalities. In this paper, we have presented a novel 3-D technique for abdominal aortic aneurysm segmentation from CTA images. The technique uses a 3-D deformable model and is implemented using the level set algorithm. Some adaptations of the level-set algorithm have been made in order to overcome specific difficulties. Experiments have been performed using CTA images of patients having abdominal aortic aneurysm. Experiments have shown good results.

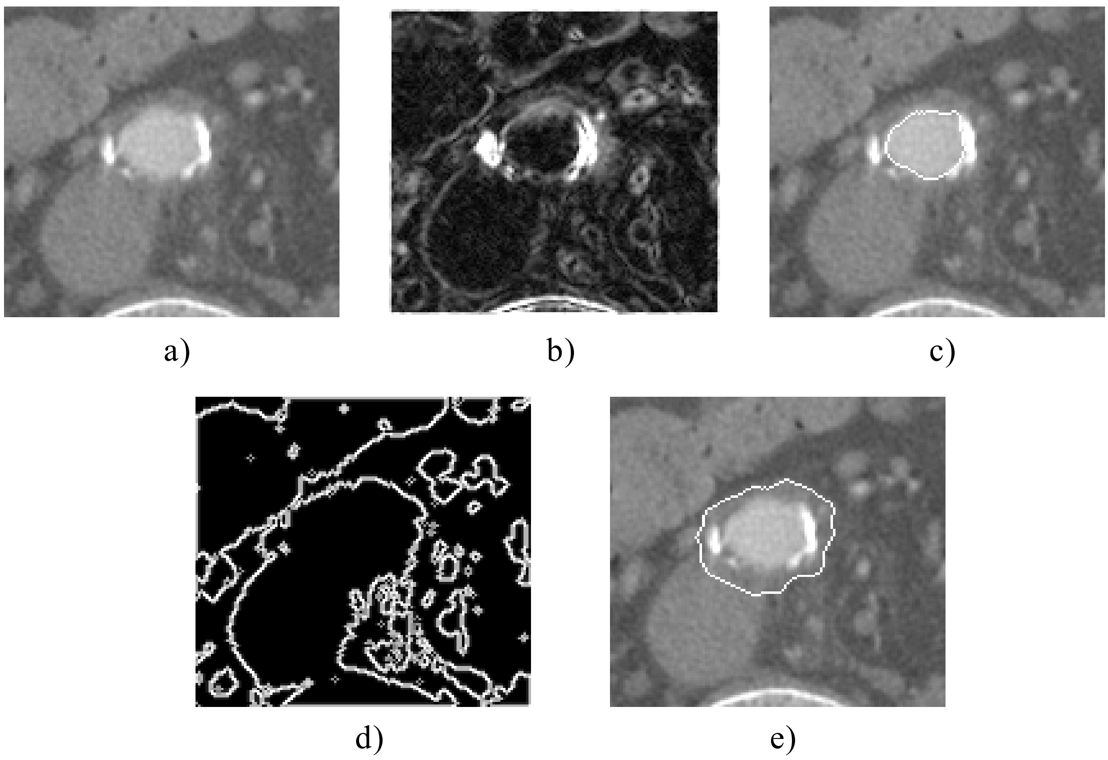

Figure 1. Segmentation results

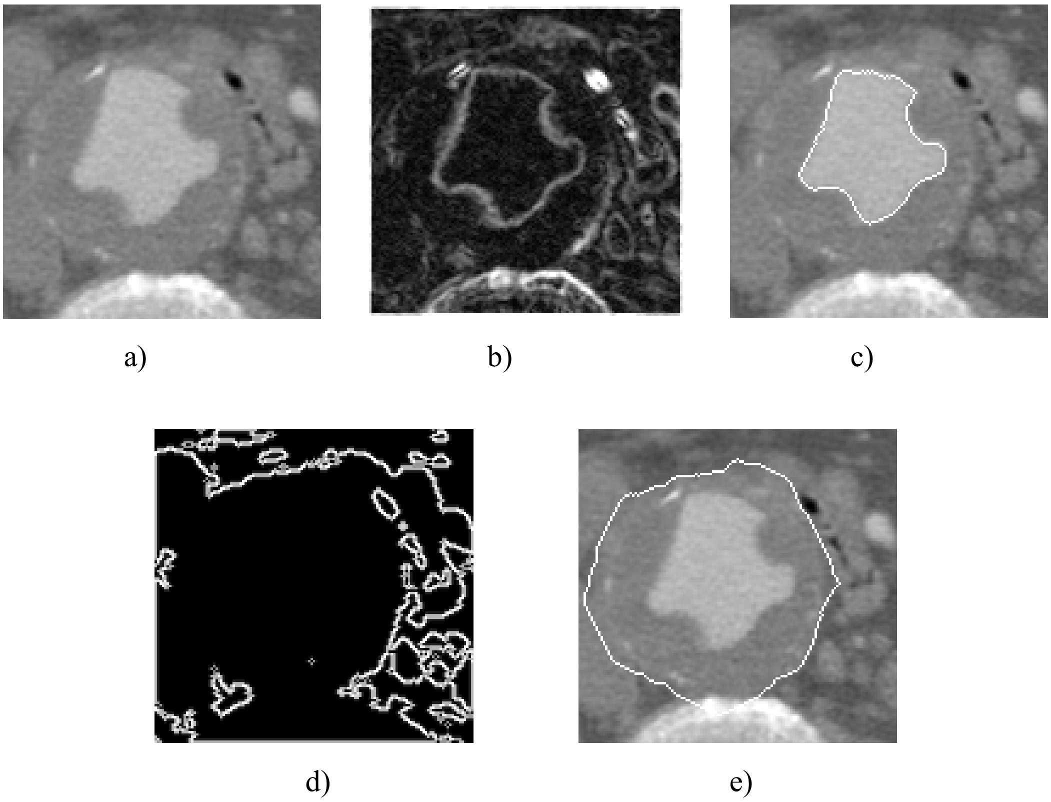

Figure 2. Segmentation results (AAA region slice)

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