Shape-Specific Adaptations for Level-Set Deformable Model-Based Segmentation

Marko Subasic[1], Sven Loncaric[1] and Erich Sorantin[2]

[1] Faculty of Electrical Engineering and Computing, University of Zagreb
Unska 3, 10000 Zagreb, Croatia
[2] Dept. of Radiology, University Hospital Graz, Auenbruggerplatz 34, A-8036, Austria

Abstract. In this paper we present two modifications to the original level set algorithm for implementation of deformable models. The modifications are motivated by difficulties that we have encountered in application of deformable models to segmentation of abdominal aortic aneurysm from computed tomography images. The level set algorithm has some advantages over the classical snake deformable models but it has difficulties with large gaps in the boundary of segmented region. Such boundary gaps may cause inaccurate segmentation that requires manual correction by the user while our goal is to keep user assistance at a minimum level. The proposed modifications have a form of additional stopping criteria. The first modification utilizes shape constraints and is less general than the second modification, which utilizes feature-based tracking of curve segments. These two modifications are developed for our specific application but we believe that they could be utilized in any similar application.

1 Introduction

Segmentation is an important and challenging step in image analysis procedures. Deformable models [7] have recently become one of the most studied techniques for segmentation, due to their ability to adapt to the specific shape of the object of interest. Following the original snake algorithm described in [8], new approaches to deformable model-based segmentation have been proposed in literature, including the level set algorithm implementation for evolution of a deformable model developed by Osher et al. [10].

The original level set algorithm, among advantages it has over classical (parametric) deformable models, has a disadvantage that it does not perform well in presence of large boundary gaps. Several modifications to the level set algorithm have been proposed [7] trying to solve this problem. These modifications alter the level set speed function utilizing energy minimization. Such speed functions can prevent deformable contour leaking trough small boundary gaps, but large boundary gaps can still cause problems for them.

In this paper we propose two modifications to the original level set algorithm for deformable models. These two modifications are designed in order to overcome the problem that the level set method has with large boundary gaps and are in form of additional stopping criterions. The modifications are motivated by our work in segmentation of medical images that always present great challenge because of high noise and imaging artifacts. More precisely, we are involved in segmentation of abdominal aortic aneurysm (AAA) from CT volume data for which we use level set deformable model [12]. AAA is a serious disorder where aortic wall becomes thicker and its physical characteristics deteriorate. Such conditions can lead to rapture of aortic wall, which presents a great danger for patient's life. AAA can be treated using minimally invasive techniques. Interest has emerged among physicians for accurate measurements of aneurysm. This information can be used in diagnostics, procedure planning, or in postoperational evaluation and condition tracking. This is the place in which the application we are developing makes its contribution by providing a 3-D model of abdominal aorta on which all necessary measurements can be performed. Often, there are large border gaps present in AAA image data, presenting difficulties to the original level set technique. The modifications we propose address this problem of AAA segmentation, but they can be useful for other classes of objects, too.

2 Level-Set Method for Deformable Model-Based Segmentation

The original active contour algorithm that is a parametric deformable model type [8], uses active contours (snakes). Parametric deformable models are very popular and are successfully used in image segmentation for some time. However they have several disadvantages. Most significant are the difficulties with segmentation of topologically complex structures. Other significant disadvantage is that implementation in 3-D is nontrivial.

To overcome these difficulties, geometric deformable models were introduced which are based on the level set method proposed by Sethian et al. [10], [11]. In this section, we will give a short description of level-set method in 2-D segmentation. Extension to 3-D case, which we use, is straightforward.

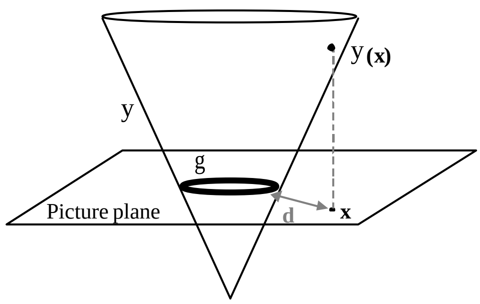

Fig. 1. Level-set algorithm illustration

In this approach for shape modeling, a 2-D curve g is represented by a 2-D function Y (Figure 1). The value of the Y at some point x is defined as a distance d of the point x to the 2-D curve g according to Equation 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 *g*(*t*=0). In this manner, *g* is represented by the zero level set *g*(*t*)= $\{x \in \mathbf{R}^2 \mid Y(x, t)=0\}$ of the level set function. The level set method then evolves the 2-D function *Y* instead of the original 2-D curve. The evolution of *Y* is described by means of a partial differential equation (PDE) shown in Equation 2.

$$\Psi(x, t = 0) = \pm d \quad (1)$$

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

$$?\ _{ij}^{n+1} = ?\ _{ij}^{n} - \Delta t F\left|\nabla_{ij} ?\ _{ij}^{n}\right| \quad (3)$$

$$F(K) = F_0 + F_1(K) \quad (4)$$

For numerical solution of the Equation 2 it is necessary to perform discretization in both space and time domains. For this purpose space coordinates are discretized using a uniform mesh of spacing *h*, with grid nodes denoted by indices *ij*. Let $?\ _{ij}^{n}$ be the approximation to the solution $Y(ih, jh, n\Delta t)$, where Δt is the time step. The expression for $?\ _{ij}^{n+1}$ can be derived using the upwind finite difference method, which gives us the final iteration expression in Equation 3. The speed term *F* depends on the curvature *K* and is separated into a constant advection term F_0 and the remainder $F_1(K)$. The advection term F_0 defines a uniform speed of front in normal direction, 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 where ε is the entropy condition which regulates the smoothness of the curve and *k* is the stopping criterion based on the image gradient as denoted in Equation 6.

$$F = k(1 - eK) \quad (5)$$

$$k(x, y) = e^{-\left|\nabla G_s * I(x,y)\right|} \quad (6)$$

where G_s*I denotes image convolved with Gaussian smoothing filter whose characteristic width is σ. This stopping criterion allows deformable model to stop on high image gradient by reducing speed function to zero, thus aligning it to the object border.

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

$$K = \nabla \frac{\nabla ?}{|\nabla ?|} = \frac{?_{xx}?_{y}^{2} - 2?_{x}?_{y}?_{xy} + ?_{yy}?_{x}^{2}}{(?_{x}^{2} + ?_{y}^{2})^{3/2}} \tag{7}$$

We use the narrow band extension as proposed by Malladi et al. [11] where the front is moved 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 d wide. During a given time step the value of Y outside the narrow band is stationary and zero level-set cannot move past the narrow band. After a given number of iterations the curve g, the level-set function, and the new narrow band are recalculated. We then calculate image-based term only inside narrow band and each Y point have image-based term based on its corresponding Gaussian gradient point.

Trading evolving curve for evolving function makes things more complex, but in return, the level-set method introduces some new qualities and resolves some problems found in the classical snake method. An important property of the level-set method is that as long as the function Y stays smooth, its zero level set can take great variety of shapes, change topology, brake and merge. Another advantage is that it is easy to build accurate numerical schemes to approximate the equations of motion.

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.

3 Modifications to the Level Set Algorithm

First we would like to describe in few words our application for segmentation of AAA so that our modifications to the original level set algorithm and problems that were motivation for their development, could be more easily understood.

The input data to our application is a consecutive series of images obtained by spiral CT scanning, which together form the volume of human abdomen. The images are obtained by angiography technique, which means that contrast agent is inside aorta during image acquisition. Use of a contrast agent during imaging provides images with high gradient at inner aortic wall (between blood flow and aorta). This is important since the utilised deformable model uses image gradient as stopping criterion. For this reason segmentation of inner aortic wall can be performed successfully with no great difficulties. A 3-D deformable model has been used for segmentation of inner aortic wall.

In addition to the inner aortic wall it is necessary to segment the outer aortic wall, too. For this task we utilise data gathered from segmentation of inner aortic wall. This task is the challenging one because surrounding tissue has similar optical density as aortic wall. In several places this surrounding tissue is leaning on aorta making it very difficult to distinguish border between them. These are the places where large boundary gaps occur. The fact that we use thresholding to eliminate internal aortic border so it would not interfere with outer aortic border segmentation only makes things worse. To restrict contour leaking to only one slice we use a 2-D deformable model on each slice in volume.

Our modifications are made to 2-D level set algorithm for deformable models that we use in segmentation of outer aortic border, although they could theoretically be extended to 3-D.

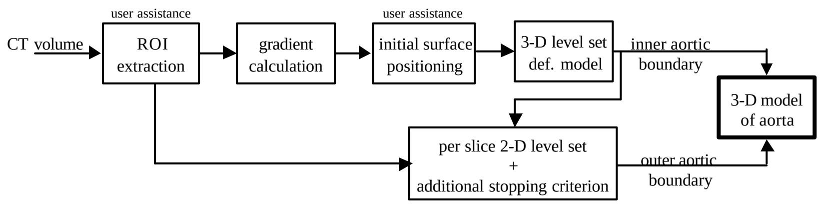

Fig. 2. Block diagram of the application

3.1 Adding Shape Constraints Using Contour-Based Shape Description

This particular additional stopping criterion is based on a prior knowledge of the aorta 3-D shape: its surface is smooth and round. Based on this fact we assume that the outer aortic boundary has same surface features in areas where it is difficult to recognize. The starting point for deformable model evolution is a circle placed over the center of inner boundary contour. This way we incorporate the presumption of aortic round shape and now the center point of inner aortic boundary estimates the center point of outer aortic boundary, which has yet to be segmented. The deformable model algorithm is then run until a predefined percentage of contour points has met outer aortic border and has stopped moving. At that point of time the additional stopping criterion is applied (Table 1.). The additional stopping criterion is basically a curve based on the original evolving curve at that point in time. The stopping criterion curve is built in the following way: point C_g is calculated as the center of mass of the inner aortic boundary contour g (Figure 2.). Then distance r from each g point from C_g is calculated. A predefined number of distances r_a is chosen based on corresponding point's angles. Distances r_a are then transformed using Fourier transformation. A 1-D low-pass filtering is then performed to eliminate higher frequency spectral components. Low frequency Fourier coefficients are then transformed back into distances r_{ift}, which are then increased by a constant amount. Distances r_{ift} define a stopping criterion curve. This way we incorporate the presumption of smooth aortic surface. In this way the stopping criterion curve estimates aortic border where it is not distinguishable in the image.

After the additional stopping criterion is calculated, evolving curvature g will stop at aortic borders and on additional stopping curve.

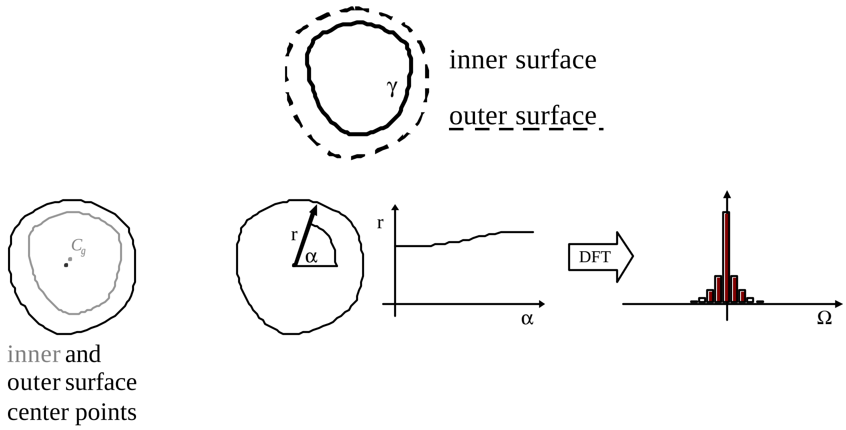

Fig. 3. Incorporation of knowledge of aortic shape into the algorithm

Table 1. The level set algorithm for outer aortic boundary segmentation

repeat for all slices
    Calculate initial surface g_{init} and initial Y
    repeat
        for i =1,...,N_{iter} **do**
            Execute iteration in Equation 3
        end for
        Recalculate curve g and narrow band
        Reinitiate Y in narrow band
        if $n_{stat}/n_{all}>M$ **then** Calculate additional stopping criterion
    until g stops changing

3.2 Feature-Based Tracking of Curve Segments

In this modification the expansion coefficient of the moving curve acts as an additional stopping criterion. Input data for this approach are CT volume and already segmented internal aortic boundary, which is an initial curve for this step. The evolving contour can be divided into moving segments, which are delimited by contour points that have already stopped. 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 8

$$X_{n+1} = X_n \times \frac{N_{n+1} + S_{n+1}}{N_n} \tag{8}$$

where N_t represents number of moving points in contour segment in given time step t and S_t represents the number of new statically points in current segment in current time step t. 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. This is not desired, so another criterion has been introduced. Only those segments are stooped whose expansion coefficient is larger than predefined value and moving point ratio R (Equation 9.) is greater then predefined level.

$$R_{n+1} = \frac{N_{n+1}}{N_n} \tag{9}$$

The moving point ratio is used to distinguish the case when we want the expansion coefficient to take action 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 getting smaller. 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.

4 Experimental results

The application has been tested using CT angiography images of a real patient. On Figure 4. some experimental results of outer aortic boundary segmentation are shown using both modification. The original slices are shown on subfigures a) and e). After thresholding and gradient operator have been applied it is easy to see large boundary gaps occurring on subfigures b) and f). Subfigures c) and g) show segmentation results for the first modification while subfigures d) and h) show segmentation results for the second modification. It can bee seen on all resulting images that in spite of the additional stopping criteria, the deformable model have penetrated slightly into the surrounding tissue, which requires some manual correction.

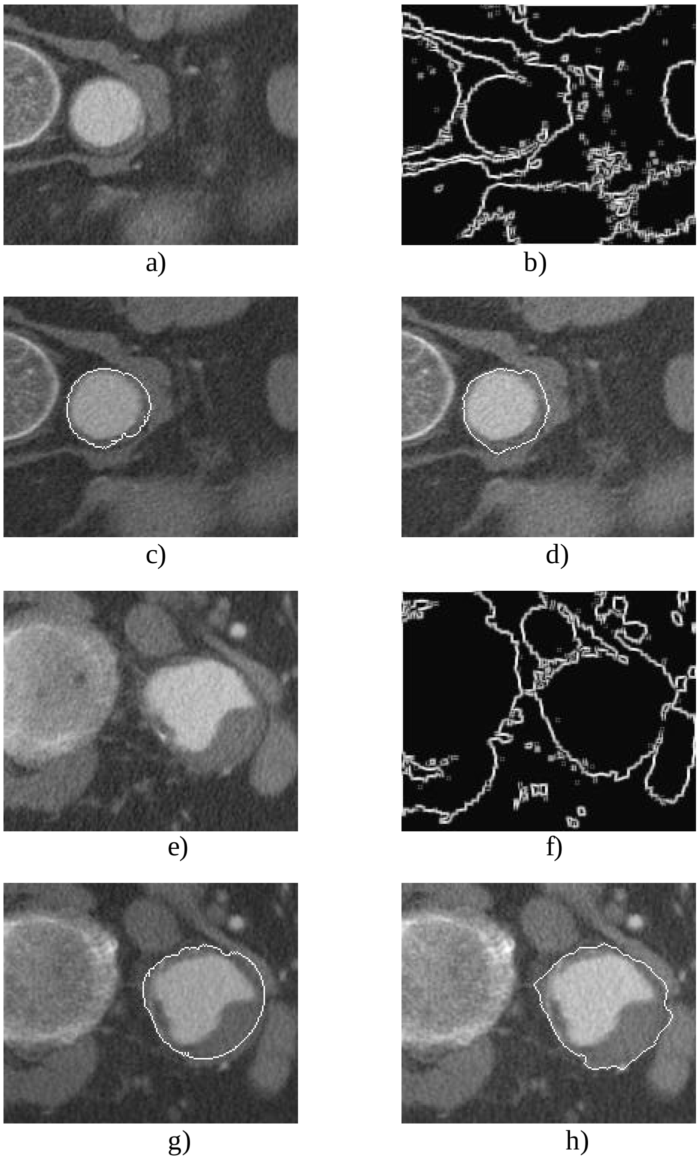

Fig. 4. Segmentation of slices with large boundary gaps

5 Discussion

Here, we described two modifications to the original level set algorithm that have been designed to solve the “boundary gap” problem, which we encountered in our application for segmentation of AAA. However these modifications do not solve the problem entirely.

The efficiency of the first modification depends largely on initial conditions that is the concentricity of internal and outer aortic boundary. It also depends on the shape and its symmetry, which is often not the case for the aortic aneurysm. In such asymmetrical cases it could happen that additional stopping curve does not encircle the entire evolving contour. The evolving curve segment that lies outside additional stopping criterion curve could then evolve unhindered.

The second modification is more general then the first one. It is capable of stopping the level set deformable model that has penetrated past the large boundary gap, from penetrating too far into surrounding tissue. This way the manual correction effort is reduced but not eliminated to the extent that we desire. The manual correction is still necessary because this modification can only stop the evolving curve when it has already missed the boundary. AAA comes in different shapes and sizes and among this variety, slices may occur that look the same to the algorithm but in fact present opposite cases and require different treatment. Our modification can not solve this problem. We feel that this is partly because our application uses plain threshold to eliminate the influence of the high image gradient found on the inner aortic border. By doing this we also eliminate already weak image gradient on the problematic areas. This produces large boundary gaps that level set algorithm has problems with.

This thought led us to believe that a more "intelligent" thresholding could solve our problem. So we direct our further investigation on applying some sort of probabilistic region labeling or boundary detection that would decrease large boundary gap occurrence and thus improve our application performance.

6 Conclusion

In this paper we have presented two modifications to the original level set algorithm for deformable models. These modifications are motivated by the problems we have encountered in the application for segmentation of abdominal aortic aneurysm. These modifications are designed to improve the level set algorithm in our specific application but we believe that they could be useful in other applications with similar difficulties. The first modification utilizes shape constraints and is less general than the second modification, which utilizes feature-based tracking of curve segments. The modifications do not solve the problems completely but they decrease undesired effects to some extent. Though the modifications introduced improvement into our application performance we feel that further improvements can be introduced, which is our next step.

7 References

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