3-D image analysis of abdominal aortic aneurysm

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ABSTRACT

This paper presents a method for 3-D segmentation of abdominal aortic aneurysm from computed tomography angiography images. The proposed method is automatic and requires minimal user assistance. Segmentation is performed in two steps. First inner and then outer aortic border is segmented. Those two steps are different due to different image conditions on two aortic borders. Outputs of these two segmentations give a complete 3-D model of abdominal aorta. Such a 3-D model is used in measurements of aneurysm area. The deformable model is implemented using the level-set algorithm due to its ability to describe complex shapes in natural manner which frequently occur in pathology. In segmentation of outer aortic boundary we introduced some knowledge based preprocessing to enhance and reconstruct low contrast aortic boundary. The method has been implemented in IDL and C languages. Experiments have been performed using real patient CTA images and have shown good results.

Keywords: Deformable model, level-set, abdominal aortic aneurysm, image segmentation, image analysis

1. INTRODUCTION

Abdominal aortic aneurysm (AAA)\textsuperscript{1–4} is a vascular disease caused by degenerative, inflammatory, mycotic diseases as well as by arteriosclerosis. It results in enlargement of the abdominal aorta due to weakened aortic wall. If left untreated AAA will enlarge over time increasing the risk of aortic wall rupture. AAA affects about 2\% of people older than 65 years. 50\% of AAAs are detected by chance\textsuperscript{3} and in up to 9\% of those patients the AAA will rupture due to weakened arterial walls. As a fatal consequence 70 - 90\% of patients with ruptured AAA will die.\textsuperscript{4}

There are various treatment options today but preferred is a minimally invasive procedure based on endovascular placement of aortic stent graft through a minimally invasive opening on the patient body. In order to perform this procedure successfully, the appropriate stent graft device has to be selected. In order to choose the stent graft of appropriate shape and size, accurate information on aortic shape and measures is required. Modern medical imaging techniques followed by appropriate image analysis methods\textsuperscript{5} have shown to be useful for measurements of AAA.\textsuperscript{6, 7}

In this paper, we present a 3-D image analysis technique for segmentation of AAA from computed tomography angiography (CTA) images. The technique is based on 3-D deformable model. The 3-D deformable model is implemented using the level-set algorithm.\textsuperscript{8, 9} The technique performs 3-D segmentation of CTA images and delivers a 3-D model of aortic wall. The 3-D model of aortic wall is extracted by separate segmenting of inner and outer aortic boundary. The segmentation of both aortic boundaries is performed by the same deformable model algorithm with only difference being in preprocessing of image data. Once the 3-D model of aortic wall is available, all measurements for appropriate stent graft selection can be performed on it.

The motivation behind our work is the need for accurate automatic segmentation which would relieve human experts of difficult, tedious and time consuming manual segmentation. The automated computer segmentation should also give higher segmentation reproducibility since results of manual segmentations tend to vary between human experts.

This work is the continuation of our previous work on the same problem. We have developed a semi automatic 3-D technique for aneurysm segmentation based on 2-D active contours with additional forces introduced for 3-D interaction between the slices.\textsuperscript{7} The technique uses the classical 2-D active contour algorithm developed by Kass et al.\textsuperscript{10} In our more recent work\textsuperscript{11, 12} we have also utilized level-set deformable model for segmentation of AAA. Inner aortic boundary has been segmented using 3-D deformable model and outer aortic boundary has been segmented using 2-D deformable model. By using the 2-D deformable model, along with some modifications to the basic 2-D level-set algorithm, we tried to overcome specific difficulties encountered in outer aortic boundary segmentation. In this work we try to solve those difficulties with some knowledge based image pre-processing.
2. DEFORMABLE MODEL SPECIFICS

In the proposed technique we utilize the level-set algorithm for implementation of the deformable model as described in papers.\textsuperscript{8, 9} We have chosen the level-set algorithm because of simple 3-D implementation and because of its ability to easily model complex structures, that can occur in aortic aneurysm area. We made two modifications to the original level-set algorithm, described later in this section, in order to reduce execution time.

![Figure 1: Evolution of 3-D deformable model inside tubular object](image)

The abdominal aorta is a tubular shaped object and the deformable model is initialized as a sphere inside the aorta (Figure 1). As level-set deformable model inflates and grows it contains more and more points. This slows down execution of iteration steps because execution time of a step is proportional to the number of deformable model points. As the deformable model inflates its points that reach the aortic wall will come to stop and deformable model will continue evolving along the aorta. After certain number of iteration steps the number of deformable model points that actually move will be roughly constant and number of points that have stopped will grow. The basic level-set algorithm runs calculation on each deformable model point, regardless whether a point has stopped or not. Extraction of points that have stopped can significantly reduce calculation time of an iteration step. We mark as stopped, points that do not change position for three iteration steps. Points extracted in each iteration step are added to the final model of aortic wall. The drawback of this approach is that some points can hold still for three iteration steps even though they have not really stopped. Those points would be eliminated from further calculations and added to the final aortic wall introducing small regions in aortic interior. Those small regions can easily be distinguished and removed later on due to their small number of points.

The second modification is made in running the deformable model on subsampled data, which is much faster. After the deformable model running on subsampled data stops, it is scaled up to fit the original sized data and used as the initialization for deformable model evolution on the original sized data. The original sized deformable model, though much slower due to greater number of points, will run only for a few iteration steps because of the good starting position.

The deformable model evolution is determined by evolution direction (inward or outward) and local curvature of the deformable model. High curvature slows down the deformable model propagation. In order for deformable model to stop on desired image objects, some form of stopping criterion is required. The stopping criterion in our method is based on the 3-D image data gradient and is shown in Equation 1

\[
k(x, y, z) = e^{-|\nabla G_\sigma * I(x, y, z)|},\]

where \(G_\sigma * I(x, y, z)\) denotes data volume convolved with Gaussian smoothing filter whose characteristic width is \(\sigma\). This Gaussian low pass filter removes some noise influence from image data. Stopping criterion of this form causes the deformable model to stop on high gradient values, which are high on object borders. Image data on which gradient is calculated is different for segmentation of inner and outer aortic boundary as will be demonstrated in the next section.

3. 3-D ABDOMINAL AORTIC ANEURYSM SEGMENTATION

The input to the segmentation method in our application is a 3-D data array built of CTA slices of the human abdomen. Before actual procedure is started, the user performs a manual extraction of the region of interest from the data volume. The region of interest is a box containing the entire AAA. This step reduces data volume thus reducing memory requirements and execution time.
The actual segmentation is performed in two independent steps (Figure 2(a)). In the first step, inner aortic border (perfused volume) is segmented and outer aortic border (unperfused volume) is segmented in the second step. The segmentation steps are made independent to allow separate segmentation of aortic borders. However, it is possible to use results from the inner aortic boundary segmentation as initialization for the outer aortic boundary segmentation which would result in execution time reduction of the entire aorta segmentation. The amount of user assistance for both step is equal and it consists of deformable model initialization. To initialize the 3-D level-set deformable model, user has to place an initial 3-D surface inside aorta. For simplicity we have chosen the initial surface to be a sphere, so the user has to manually select the center and the radius of the sphere on one slice. Initialization has to be done so that entire initial sphere resides inside aorta because the deformable model can only be inflated (propagated outwards). Due to this initialization is usually performed on upper part of the abdominal aorta, before the bifurcation. The smaller sphere is easier to place, but the radius must not be too small because high curvature of the small sphere could prevent evolution of the deformable model. On the other hand selecting largest possible radius would require more effort and would not result in significant speed gain because several first evolution steps are very fast due to small number of points that make the deformable model. The same initialization, if properly done, can be used for both segmentation steps.

### 3.1. Segmentation of inner aortic boundary

Initialization for this segmentation step has to be done so that entire initial sphere resides inside inner aortic boundary because the deformable model can only be inflated. The stopping criterion for level-set deformable model in this step is based on the 3-D gradient of CTA slice images. The contrast between aortic interior and aortic wall is very high due to angiography technique used in image acquisition. This makes gradient values particularly high on inner aortic border (Figures 4(b), 5(b)). Such high gradient can efficiently stop deformable model evolution on inner aortic boundary.

After initialization the level-set algorithm is activated and it runs automatically until all deformable model points have stopped. Depending on the elasticity coefficient, that determines curvature influence on deformable model evolution,
the deformable model can go through the bifurcation. The output of this segmentation step is the computer model of inner aortic boundary which consists of all points laying on inner aortic border. The model built from point set can subsequently be transformed into parametric form more suitable for user interaction. The basic implementation of 3-D level-set deformable model performs very well and requires no modification because of good image conditions in this segmentation step. Use of a level-set deformable model is very convenient because inner aortic border shape in aneurism area can vary greatly from natural oval shape.

3.2. Segmentation of outer aortic boundary

In segmentation of outer aortic boundary we also utilize 3-D level-set deformable model but the image conditions in this step are not as good as in previous one. The main problem comes from the fact that the tissue surrounding the aorta has similar optical density as aortic wall. In several places this surrounding tissue comes very close to the aorta (Figures
This makes it very hard or even impossible for image processing algorithms to determine the border between them. Even for human experts it is not an easy task. Such contact areas produce gaps on the aortic boundary. The level-set algorithm can successfully deal with small boundary gaps thanks to its local curvature based speed term, but cannot stop its propagation into surrounding tissue in places where the boundary gaps are large. Some modifications to the level-set algorithm, aiming the boundary gap problem, have been suggested, but none of them has the ability to handle large boundary gaps appropriately. To overcome this difficulty we introduce knowledge based, per slice pre-processing to restore missing or weak edges and thus close or reduce large boundary gaps.

Plain image data gradient can not be used as input data for deformable model in this step. This is due to the above mentioned problem and due to high contrast on inner aortic boundary. The inner aortic boundary would then interfere with deformable model causing it to stop on inner aortic boundary, not even reaching the outer boundary. To eliminate inner boundary influence in our previous work we used thresholding as data pre-processing. The problem is that plain thresholding can not eliminate large boundary gaps, in fact it can even make things worse by leaving out edges that exist but are very weak.

In this work we suggest several pre-processing steps (Figure 2(b)) to eliminate large boundary gaps. The pre-processing starts on the slice that deformable model initialization was performed on and moves both up and down trough the data volume. These pre-processing steps with resulting figures are shown in Figure 3. First we apply local thresholding to image data where the background is assigned value of 1 (Figure 3(b)). Local thresholding is used in order not to leave out weak edges. To this data we superimpose the thresholded image gradient data (Figure 3(c)), which is also a way to highlight weak edges. Here, image gradient is thresholded with two threshold values. The lower threshold is used to eliminate noise influence, and higher threshold is used to eliminate inner aortic boundary gradient. From this data, connected regions are calculated and small regions are discarded. This leaves us with the background of the slice (Figure 3(d)). Zero pixels represent the foreground in which lies our object of interest: abdominal aorta. On those foreground pixels we also build connected regions, and again discard connected regions with low number of pixels (Figure 3(e)). Those small regions removals should eliminate small regions induced by noise. There should now be one or more large regions left and one of them should be the abdominal aorta.

The region that represents the abdominal aorta is chosen to be the region, which overlaps the most with aorta region from previously processed adjacent slice. This works well for all slices except the first one to be processed, which is the one, that initialization was performed on. On the first slice to be processed the aorta region is selected as the region in which the center of initial sphere is placed by the user.

Our application also utilizes one additional information that human experts also use to estimate outer aortic border where not distinguishable. Some calcification, that is clearly visible on CT scans, occur inside aortic wall close to outer aortic boundary. If such calcification would occur close to weak border than it could be used to estimate at least the part of that weak border. We extract those calcifications by thresholding and use them to enhance outer aortic boundary (Figure 3(f)). In areas where border already exists this intervention makes no difference, but in areas where boundary has not been detected it can restore the boundary. This way the chances of large boundary gaps elimination are increased.

So far we have the aorta region with reduced large boundary gaps, but previous steps are not sufficient to completely eliminate boundary gaps especially very large ones on all slices. Those large boundary gaps would produce extra region parts that represent surrounding tissue. Now it is required to remove those extra regions. For that we use some knowledge based image processing. We exploit the fact that the outer aortic boundary is convex in most cases and that large boundary gaps would cause such convex aortic shape to become concave. The next processing step is based on the distance map of background image (Figure 3(g)). On the distance map, gradient is calculated along lines coming from aortic center. Aortic center is found as the point with maximum distance in aortic region. Such gradient is negative inside object region because distances are decreasing as we move further away from center and closer to the boundary. A large concavity (caused by large boundary gap) on object border would cause the gradient to turn positive. The points where this distance gradient is positive are removed from the object (Figure 3(h)). This way we estimate the weak border and close large boundary gaps. This approach has problems when boundary gap axis (a line drawn trough the middle of the gap) passes close to the aortic center that we use. In this case the border would not be restored in the proper manner. To deal with such cases we calculate distance gradient for several center points, which are few pixels apart from maximum distance point. We then build object regions based on each of those distance gradient maps. The combination of those object regions produces final object region for the slice, on which the weak boundaries are restored correctly.
### Table 1: Comparison results for all slices

<table>
<thead>
<tr>
<th>result sets compared per slice</th>
<th>correlation</th>
<th>average relative error [%]</th>
<th>standard deviation [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>proposed automatic segmentation &amp; manually corrected automatic segmentation</td>
<td>0.93</td>
<td>12.35</td>
<td>13.92</td>
</tr>
<tr>
<td>proposed automatic segmentation &amp; manually corrected semi-automatic segmentation</td>
<td>0.91</td>
<td>19.75</td>
<td>13.29</td>
</tr>
<tr>
<td>manually corrected automatic segmentation &amp; manually corrected semi-automatic segmentation</td>
<td>0.99</td>
<td>14.71</td>
<td>8.18</td>
</tr>
</tbody>
</table>

The resulting object region could still have some small gaps in it and edges might be wrinkled so we apply morphological opening to obtain final object region for the slice (Figure 3(i)).

After all slices are processed we have a binary volume representing abdominal aorta. Such region still can have some smaller boundary gaps so the segmentation is still not complete and it makes sense to apply a deformable model algorithm. We apply the same 3-D level-set deformable model as in the segmentation of the inner aortic border. The stopping criterion for the deformable model algorithm, in this segmentation step, is based on the edge of the above mentioned binary volume. The output of the algorithm is a computer model of outer aortic boundary.

3-D models of inner and outer aortic boundary, together make a complete model of aortic wall. This data can be used as input for many other applications like visualization, measurement, condition tracking etc.

### 4. RESULTS AND DISCUSSION

The proposed method has been tested using CTA images of real patients. Figures 4 and 5 show sample segmentation results for two slices. Subfigures (a) show slices of input data. Subfigures (b) show gradient images used for inner aortic boundary segmentation. It can be seen that image gradient is much higher on the inner aortic border than on the outer. Subfigures (c) show segmented inner aortic borders over the original slices. Results of plain threshold applied to the original slices are shown on subfigures (d) and it can be seen that relatively large portions of outer aortic borders have been lost so that large boundary gaps have had occurred. In subfigures (e) the gradient images of input data for outer aortic boundary segmentation are shown. The input data images are obtained trough pre-processing described in Section 3.2. Subfigures (f) show outer aortic boundary segmentation results and it can be noticed that the proposed method have successfully "closed" large boundary gaps. The pre-processing described in Section 3.2 favors convex shape of outer aortic boundary. On most slices abdominal aorta is convex (healthy aorta always is) so such slices would be properly pre-processed. On exceptional slices where abdominal aortic aneurysm has significant concavities, the method would not perform accurately. Such aortic regions would most likely be cut of to make aortic region convex.

The method was tested on 11 real patient datasets. On each dataset three groups of segmentation results were obtained:

1. results from segmentation performed using the proposed automatic method
2. segmentation results from the above automatic segmentation method manual correction by a human expert
3. results from segmentation performed using the semi-automatic method described in" that were manually corrected by a human expert.
Table 2: Comparison results grouped by patients

<table>
<thead>
<tr>
<th></th>
<th>proposed automatic segmentation &amp; manually corrected automatic segmentation</th>
<th>proposed automatic segmentation &amp; manually corrected semi-automatic segmentation</th>
<th>manually corrected automatic segmentation &amp; manually corrected semi-automatic segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>correl. av. err. % std. dev.</td>
<td>correl. av. err. % std. dev.</td>
<td>correl. av. err. % std. dev.</td>
</tr>
<tr>
<td>1</td>
<td>0.99 6.91 2.82</td>
<td>0.99 19.01 5.34</td>
<td>0.99 17.96 6.56</td>
</tr>
<tr>
<td>2</td>
<td>0.90 12.32 13.75</td>
<td>0.78 21.66 14.20</td>
<td>0.95 15.50 6.46</td>
</tr>
<tr>
<td>3</td>
<td>0.73 33.50 16.82</td>
<td>0.74 38.40 11.33</td>
<td>0.99 13.46 5.80</td>
</tr>
<tr>
<td>4</td>
<td>0.62 20.71 24.37</td>
<td>0.60 28.66 22.92</td>
<td>0.99 12.36 10.81</td>
</tr>
<tr>
<td>5</td>
<td>0.62 16.25 14.14</td>
<td>0.58 17.82 12.19</td>
<td>0.98 9.12 3.22</td>
</tr>
<tr>
<td>6</td>
<td>0.87 9.34 10.09</td>
<td>0.87 18.22 13.75</td>
<td>0.99 12.83 8.50</td>
</tr>
<tr>
<td>7</td>
<td>0.98 10.20 6.67</td>
<td>0.99 14.46 5.66</td>
<td>0.99 12.58 6.21</td>
</tr>
<tr>
<td>8</td>
<td>0.84 13.61 12.83</td>
<td>0.90 17.00 10.42</td>
<td>0.96 14.30 8.53</td>
</tr>
<tr>
<td>9</td>
<td>0.98 11.42 8.83</td>
<td>0.99 12.58 6.15</td>
<td>0.99 18.86 8.77</td>
</tr>
<tr>
<td>10</td>
<td>0.79 8.17 2.98</td>
<td>0.73 20.74 4.18</td>
<td>0.70 23.98 4.37</td>
</tr>
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<td>11</td>
<td>0.99 3.90 4.33</td>
<td>0.93 19.31 7.74</td>
<td>0.93 16.77 6.24</td>
</tr>
</tbody>
</table>

These three groups of the segmentation results were cross-compared. Since our goal is to produce correct segmentation on each data slice, all comparisons were performed on per slice basis and average values were calculated for each patient and for all patients. Comparison results for all slices are shown in Table 1 and comparison results grouped by patients are shown in Table 2. Statistical correlation coefficients for the proposed automatic segmentation method compared to two manually corrected results in Table 1 are both above 0.9 indicating a good correlation. Statistical correlation coefficient between two manually corrected segmentation result sets is high 0.99 which is expected. The total pixel difference between two segmentation methods on a slice is used to calculate relative segmentation error. The last two groups of the segmentation results, manually corrected automatic segmentation results and manually corrected semi-automatic segmentation results, are both approved by human experts and are presumed to be correct. The relative error of the proposed automatic method is calculated compared to the both "correct" groups of the segmentation results. The average relative error of the automatic segmentation results compared to the manually corrected automatic segmentation results for all segmented slices (Table 1) is 12.35% with standard deviation of 13.92%. The average relative error of the automatic segmentation results compared to the manually corrected semi-automatic segmentation for all segmented slices is 19.75% with standard deviation of 13.29%. The above difference of relative errors can be explained by the fact that both "correct" segmentation results are produced by manual correction of results of the two different segmentation methods. Such manual corrections are known to be a tedious, exhausting and subjective task so results can be erroneous. Also, manual corrections on two "correct" results groups were performed by two different human experts using two different computer graphical user interfaces which can also induce different results. Both relative errors are pretty high and accuracy achieved probably would not suffice for clinical use. However, it is interesting to notice that relative error between two "correct" segmentations is 14.71% with standard deviation of 8.18%. This relative error is between two results that are both accepted as correct and one can notice that it is comparable to the relative errors of the proposed automatic segmentation method. This may imply that, although calculated average relative error of the proposed automatic algorithm appear to be high it may be that the actual performance is somewhat better due to the validation problem which is very well known in medical imaging.

5. CONCLUSION

In this paper we presented a method for segmentation of abdominal aortic aneurysm from CTA images. The application utilizes a 3-D deformable model implemented using the level-set algorithm. Segmentation is performed in two separate steps for inner and outer aortic boundary. Method requires minimal user assistance in deformable model initialization.
Some specific difficulties have been encountered in outer aortic boundary segmentation and we introduced some knowledge based pre-processing to address those difficulties. The method delivers a 3-D model of abdominal aorta. On a computer model of abdominal aorta different measurements can be performed. Information gathered in this way has many applications wherever the knowledge of aortic shape and size is required. Possible applications are diagnostics, minimally invasive procedure planning (stent graft selection) and post-operative condition tracking. Advantages of an automatic segmentation are increased reproducibility and relieving the human experts of tedious work. Experiments have been performed using CTA images of real patients. Results of the proposed method have been compared to two “correct” result-sets approved by human experts. It has been observed that the difference between proposed methods results and “correct” results is comparable to the difference between two “correct” results.

REFERENCES

Figure 4: Segmentation results I

Figure 5: Segmentation results II