Strategies for Robust Aortic Arch Segmentation and Analysis in CTA Images

K. López-Linares[1,2], I. Macía[1,2], and J.H. Legarreta[1,2]

[1] Vicomtech Foundation, San Sebastián - Donostia (Spain)
http://www.vicomtech.org
[2] Biodonostia Health Research Institute, San Sebastián - Donostia (Spain)
http://www.biodonostia.org

klopez@vicomtech.org

Abstract. The automatic segmentation and analysis of the aortic arch as well as its branches is of vital importance for Thoracic Endovascular Aneurysm Repair (TEVAR) interventions. This paper explores different possibilities and approaches to the segmentation and vascular analysis of the thoracic aorta in Computed Tomography Angiography (CTA) images that is suitable for clinical practice. Our goal is to present the encountered problems and future possible solutions to obtain a fast, automatic, robust and accurate method based on front propagation algorithms.

Keywords: Aorta, thoracic, arch, segmentation, CTA, vessel analysis, region growing, fast marching, aortic arch, front propagation

1 Introduction

The segmentation and analysis of the thoracic aorta is of vital importance for the diagnosis and treatment planning of cardiovascular diseases, reducing the workload of physicians. Lately, an increasing number of aortic pathologies are treated by semi-invasive procedures by deployment of stent grafts chosen or custom-designed depending on the anatomy of each patient. Therefore, an accurate segmentation and vascular analysis of the aorta and its branches is crucial for a successful intervention and to avoid post-operative complications. The location and distance between the innominate, left common carotid and left subclavian arteries and other morphological parameters such as vessel diameters, curvature and length of the pathology along the centerline and along inner and outer contours are needed for a complete vascular analysis. However, the segmentation of the aortic arch and its branches is not a trivial task, since it frequently merges with adjacent structures of similar image intensity such as the heart chambers or the pulmonary arteries.

Several methods have been proposed for aortic arch segmentation and analysis from CT (Computed Tomography) images. Researchers from the University of Heidelberg focus their work in model-based segmentation approaches. In [1] they introduce a 3D cylindrical intensity model which is fitted to the image intensities through a segment-wise process based on a Kalman filter to extract model parameters. The method is not well suited for pathologies and bifurcations so in [2] they improve it to segment the supraaortic branches by analyzing the connected components within a spherical volume around the vessel. In [3] they restrict the segmentation between two points in the descending and ascending aorta respectively, avoiding leaks to the heart tissue, which is later refined by a two-step procedure. The proposed model may be inaccurate in the case of non-circular cross sections. In [4] and [5] they combine the model-based segmentation approach with elastic registration, resulting in a deformation field which is used to compute a refined vessel contour and centerline, at a higher computational cost. Feuerstein et al. [6] describe a method based on Hough and Euclidean distance transforms and probability weighting that works both for contrast enhanced and non-enhanced datasets. To segment the branches they apply a parallel projection of the boundary of the segmented aorta and a likelihood driven branching assignment. Aortic arch segmentation based on the Hough transform has also been proposed in [7], [8] and [9].

Our aim is to develop a robust and accurate method for the thoracic aorta and branch segmentation, which works both for pathological and healthy aortas. We seek for a method that is practical in clinical settings: flexible, fast, semi-automatic and that does not require deformations or registrations of a rigid model due to initialization, speed or robustness issues. We discard also Hough transform based segmentation due to anatomical variations. The ability to automatically detect the heart is also pursued for a future full automation and better reproducibility. This paper summarizes our ongoing work in developing such a method, starting with an adaptive region growing approach, successfully applied to the segmentation of the abdominal aorta in [10]. The outline of the paper is as follows: in Section 2 several approaches and the encountered problems are presented. In 2.1 we analyze a previously developed adaptive region growing algorithm. As an evolution of this, in 2.2 a topology-constrained front propagation algorithm with simultaneous vessel analysis is proposed. In 2.3 a fast marching approach is explored. Finally, in Section 3 we present our preliminary results and in Section 4, the encountered problems and possible solutions for future work are discussed.

2 Aortic Arch Segmentation

In this section we present three methods for thoracic aorta and branch segmentation from 3D CTA datasets: adaptive region growing, topology-constrained front propagation and fast marching. The challenge when using any of the three algorithms is to adapt to shape or intensity inhomogeneities along the vessel and to stop the evolution of the algorithm when the heart is reached, which hinders the automation of the segmentation.

2.1 Adaptive Region Growing

Firstly, we have applied to the thoracic case the region growing method proposed in [10] for abdominal aorta segmentation. The method starts from a user-selected seed point in the lumen of the aorta and it iteratively includes pixels that meet a certain intensity inclusion criteria based on local statistics. The algorithm keeps a buffer and the inclusion criterion is recomputed based on statistics of the pixel intensities whenever the buffer fills, allowing to adapt to intensity inhomogeneities along the aorta. However, this method is not appropriate for the study case since it leaks into the heart tissues as the growth is only controlled by image intensity. This also poses an efficiency and speed problem, since the algorithm requires a long time to visit all the pixels before stopping.

2.2 Topology-Constrained Front Propagation

To solve the previous problems, a topology-constrained front propagation method is proposed, that iteratively segments a region of the aorta and computes vascular descriptors such as the centerline and cross-section diameters. The idea is to allow a more effective control over the evolution of the front, by analyzing each vascular segment before continuing with the growth, i.e. by geometrical and topological analysis of centerlines. Thus, the algorithm could be stopped when the heart is nearby or may prevent partial segmentations in presence of obstacles. The initial hypothesis is that since the thoracic aorta is large, the algorithm will evolve preferentially in the radial direction rather than longitudinally. At each iteration, we extract a voxel-based centerline of the segmented vessel region by skeletonization via distance-based homotopic thinning. Then, a vessel graph structure is created from the raw skeleton which is used to prune spurious branches and loops and smooth the centerline (see details for these methods in [10]). The average diameter of the aorta is computed by a ray-casting strategy on extracted centerline cross-sections.

We detected that the instability of the centerlines compromises the algorithm performance. The 3D skeleton contains some spurious branches as a result of the irregularities of the boundaries of the segmentation, which leads to inaccurate computation of sections and radii. To improve the results and speed up the computations, we apply a three-level multiresolution pyramid to get a smoother mask before computing the centerlines. This leads to a better scale selection allowing to more accurately estimate the vessel center, sections and diameters. However, the algorithm grows in a unequal manner radially, and hence, when it stops at each iteration the top of the obtained region is sometimes uneven. When this happens, the sections and radii obtained are discarded and recomputed in the next iteration. The aim is to have a knowledge of the front evolution anytime and hence, being able to define a certain criterion to stop its propagation when the heart is nearby. We have explored the applicability of the following two criteria. On one hand, the goal is to detect a discontinuity in the diameter when the heart is reached (see Fig. 1). On the other hand, we know that the ascending aorta is shorter than the descending one. If we define the descending height (h_d)

as the perpendicular distance between the celiac trunk and the top point in the aortic arch, and the ascending aortic height (h_{a}) as the distance from the top in the aortic arch to the beginning of the unstable region close to the heart, we can compute the ratio of the respective heights for each patient and utilize it as the stopping criterion. The results of these experiments are summarized in Sect. 3.

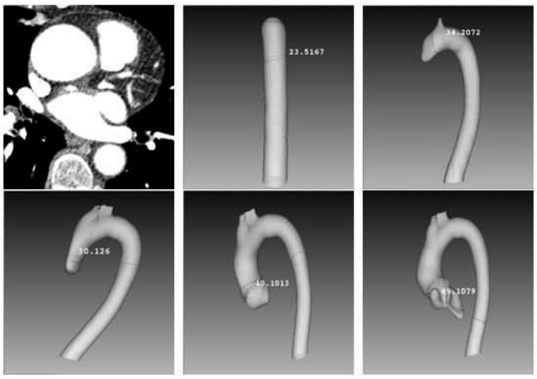

Fig. 1: Topology-constrained front propagation algorithm steps and original ROI

2.3 Fast Marching Segmentation

The fast marching method is a numerical method for solving boundary value problems. It describes the evolution of a closed surface as a function of time, following a typical front-propagation schema with a certain speed function. If the speed function is equal to one, the algorithm computes a distance map. Providing an edge-based speed function to control the evolution of the front a segmentation can be obtained. Applying the implementation from [11] that is based on [12], from a seed point in the descending aorta and a speed function computed from an edge map, the fast marching systematically moves the front forward along the aorta.

First we process our CTAs by applying an anisotropic diffusion filter to reduce noise, followed by a gradient Gaussian function computing edges at a proper scale. We set the speed image as a sigmoid function of the previous edge map, such that the propagation speed of the front is low close to high image gradients while it moves faster within the aorta. The output of the algorithm indicates the time it takes for the front to arrive at each pixel location. It is expected that the contour takes a longer time to cross over the edges, resulting in large changes on the time-crossing map values close to the structure edges. The algorithm terminates when the current arrival time being processed is greater than a stopping value. The segmentation is obtained by thresholding the output, locating a time range in which the contour was contained for a long time inside the aorta.

The algorithm principally relies on the α and β parameters that define the transformation to be applied by the sigmoid. These parameters are used to enhance the differences between regions of low and high values in the speed image. The heuristic for finding these values is based on observing the intensities of the gradient magnitude image of each dataset. The values depend on the mean intensity value inside the aorta and the minimum value along its contour. In a first approach, we have selected α and β manually. Then, we have tried to automatize the process of finding the sigmoid parameters. We have applied region growing to a number of voxels in the descending aorta and from the gradient image of this segmentation we have calculated α and β, which leads to a complete automation of the algorithm parameters.

3 Experiments and Results

We have presented three different methods for thoracic aorta segmentation, concluding that the fast marching approach yields the best results and segments correctly branches and (spurious) pathological structures. The algorithms, developed in C++ as extensions of the ITK libraries [11], where tested in 12 CTA datasets, including those showing aneurysms, obtained from different manufacturers (Siemens, Toshiba and GE) and whose spatial resolution vary between 0.79 and 0.97, being able to evaluate the robustness of the proposed methods.

Fig. 2a shows the result of the segmentation of a reference dataset with the adaptive region growing algorithm. Since it only relies on image intensity values, the growth extends to the heart tissues and no correct segmentation is obtained. This led us to propose the topology-constrained front propagation algorithm, which incorporates a stopping criterion depending on the anatomy of the aorta. After running the method on a reference CTA dataset for several iterations, we observed that, as expected, the ascending aortic diameter was larger than the descending diameter, as shown in Fig. 3. The peaks are related to the sections in the upper area of the heart. When applying the same algorithm to other datasets, however, we concluded that this evidence is not clear for many cases due to anatomic variations. In a second approach, we calculated the relation between the ascending aortic and descending aortic heights as defined in Sect. 2.2: $h_{\mathrm{d}}/h_{\mathrm{a}}$ ranges between $1,69 < h_{\mathrm{d}}/h_{\mathrm{a}} < 2,645$. We computed the average $h_{\mathrm{d}}/h_{\mathrm{a}}$ and run the algorithm following that stopping criterion. However, the results were not as expected, since the range of $h_{\mathrm{d}}/h_{\mathrm{a}}$ is wide and the average does not approximate correctly the value in each case. A heuristic or classification scheme that combines diameter, height and additional parameters in a rule that applies to a significant number of cases is to be investigated.

Regarding the fast marching approach, by manually entering the sigmoid parameters the algorithm segments correctly 9 out of 12 datasets. In the remaining three it segments the arch but only an area of the ascending aorta, which is enough for most of the applications. A visual inspection reveals that it has a high accuracy in segmenting the vessel boundaries along all its trajectory. The stopping time and the threshold have been experimentally set to 300. We have detected that the evolution is very sensitive to the sigmoid parameters and the position of the initial seed point along the aorta. Thus, we request the user to

Fig. 2: Segmentation of reference dataset with a) Adaptive region growing, b) Topology-constrained front propagation, c) Fast marching

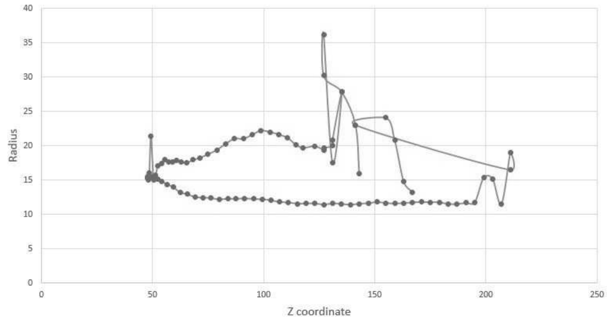

Fig. 3: Aortic radius versus z coordinate of each cross-section centerline point in reference CTA

place the seed right above the celiac trunk, which is a good anatomical reference. To avoid problems with the setup of the sigmoid parameters, we have automatized their extraction as explained in Sect. 2.3. The algorithm works correctly for 8 out of 12 cases. In the remaining 4, it either stops growing long before reaching the heart or it leaks into it. This is due to the intensity changes along the aorta, which are not considered when computing α and β only taking into account an area of the descending aorta. Both the manual and the semi-automatic methods are very fast on a standard desktop computer: they take on average 10 s, 15 s ,respectively, versus the 90 s of the topology constraint front propagation approach. Figure 4 shows the results of the fast marching algorithm when the parameters are set manually.

4 Discussion and Future Work

We have tried three approaches for thoracic aorta segmentation starting from a seed point in the descending aorta. The adaptive region growing algorithm is fast and accurate, but it fails to stop when the heart is reached. A practical possibility is to introduce another seed point in this region but this approach sometimes fails leading to lengthy calculations due to unexpected leaks and avoids to improve the overall automation and reproducibility. The topology-constrained front

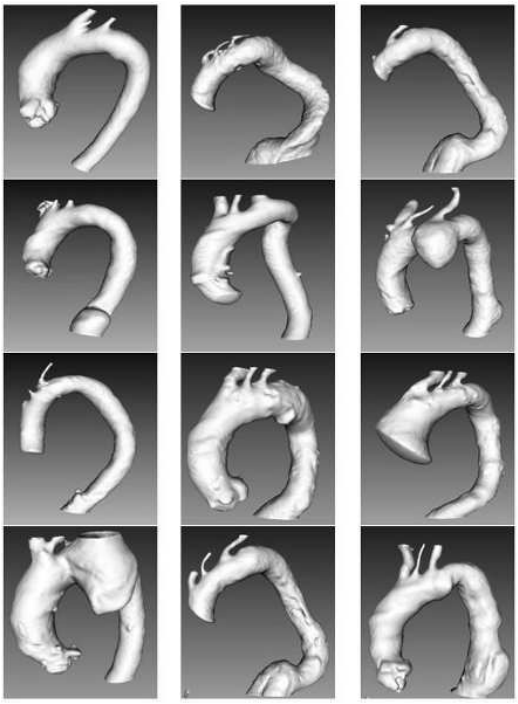

Fig. 4: Fast marching algorithm results with manual setup of parameters

propagation should provide the ability to define a stopping criterion based on the patient-specific aortic anatomy, which can be implicitly known during the segmentation progress. However, it remains a challenge defining a rule based on features, since the thoracic aorta is a large structure that at the local level and finest scale may not be considered as tubular. We tried to apply the hypothesis that the aortic diameter steadily grows to a maximum when the heart is found, but patient dissimilarities make this inapplicable. For the same reason, we observed that a patient-specific relation between relative heights of celiac trunk, aortic arch and heart also failed. Therefore, we think that an heuristic rule or a supervised classifier based on a set of additional descriptors could be a solution. It is important to notice that instabilities in the centerline greatly affect the performance of this algorithm. To overcome this drawback we have applied a multi-resolution pyramid, but it compromises the accuracy when segmenting the aortic branches. A multi-scale centerline extraction or a shaped constrained centerline topology as proposed in [13] could solve these complications.

On the other hand, the fast marching algorithm is very fast and yields very accurate results, correctly segmenting all branches and datasets with pathologies. Nonetheless, it is very sensitive to the sigmoid function parameters used to create the speed image and the algorithm stopping time. Some authors have dealt with this issue in 2D and have proposed CTA-specific speed control functions and stopping criteria [14]. An adaptation of this method for 3D will be investigated.

Despite the fast marching method gives some consistent results, there are still problems to solve due to the speed function. We think that a region growing algorithm, growing in a front propagation manner similar to the fast marching could be a feasible solution. Finally, we expect to perform a quantitative evaluation comparing these methods and manual segmentation by experts in a large number of datasets from different scanners to further assess the accuracy and reproducibility of the methods.

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