Adaptations of MARACAS algorithm to the segmentation of the carotid bifurcation and stenosis quantification in CTA images

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Abstract

This carotid-bifurcation segmentation and stenosis quantification method uses one seed-point per vessel. Each seed-point initializes the extraction of one centerline by use of an algorithm based on an elastic model and on a multi-scale eigen-analysis of the inertia matrix. This algorithm requires that the vessels be brighter than the background. The initial image is transformed and enhanced by a three-stage filter, in order to comply with this requirement: 1) extraction of regions falling into the typical vascular lumen range, 2) refinement using a Fuzzy C-means classifier, and 3) enhancement using gradient magnitudes and an exponential function. The method was evaluated on 31 datasets from the Carotid Bifurcation Algorithm Evaluation Framework and the segmentation results obtained an average of 80.4% Dice similarity score, copmared to reference segmentations, and the mean stenosis quantification error was 14.4%.

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This paper describes a 3D CTA image segmentation method submitted to the CLS09 contest (Carotid Lumen Segmentation and Stenosis Quantification) held in conjunction with the MICCAI 2009 conference (http://www.miccai2009.org/). Figure 1 presents the pipeline of the proposed methodology. Initially, images are denoised to improve image quality and posterior segmentation. Second, region-based measurements are performed to differentiate possible vessels from other structures. Then, edge-driven metrics are used to allow vessel separation from nearby structures. Using, both edge-driven and region-based metrics a filter is used to enhance the vessels. The vessels of interest are extracted by use of the provided initialization points and of a model-driven segmentation algorithm. Using the obtained result, the final stage is devoted to stenosis quantification.

1 Image intensity-based preprocessing

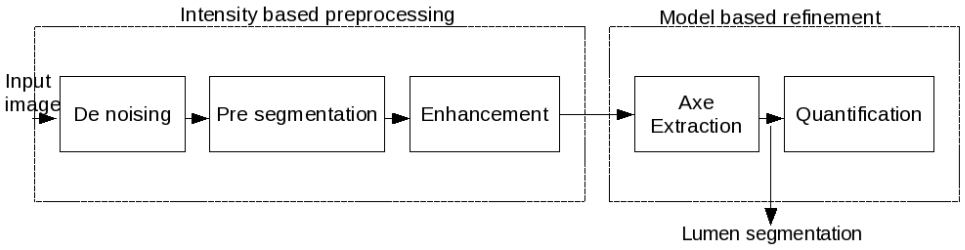

Figure 1: Carotid lumen segmentation and stenosis quantification framework.

Denoising

Segmentation algorithms are often sensitive to image degradations. Unfortunately, CT-scans are prone to noise and artifacts. Thus, to increase the segmentation rate, our algorithm preprocesses the images. A χ^2 test revealed that the noise is Gaussian. To reduce it, we use a robust NL-means approach [1]. The quasi constant piecewise nature of the CT scans enables to decrease the robust criterion, and thus consider only sample pixels belonging to the same object as the pixel to be denoised. Hence, as in [1], a gaussianity test is performed on each sample pixels set. When the null hypothesis of the test is true, the output pixel is set as the mean gray-value of the sample set. In few cases, when the opposite occurs, a local constant regression gives the output pixel. Streak artifacts are mainly visible in the section of the patients'shoulders. They are due to the high absorption of photons when the signal crosses a large body section. On the images, they are oriented in between -20 and 20 degrees. In our algorithm a Dual Tree Complex Wavelet Transform (DT-CWT) [4] decomposes the image following 6 different directions. The streak artifacts impact on the coefficients associated to the -15 and 15 degrees oriented wavelets and at different scales. These coefficients are shrunk using a hard threshold. In the other four directions, the corresponding wavelet coefficients are threshold following a bi-shrink approach [4], only to remove noise.

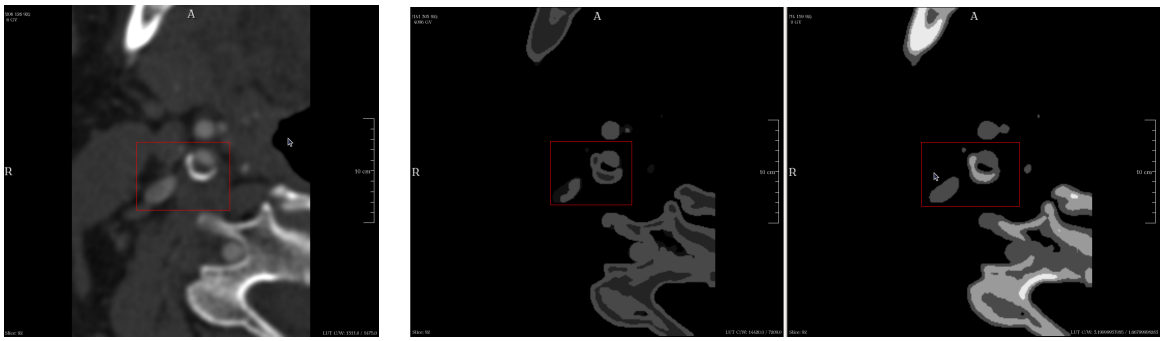

Figure 2: **Left**: Original slice. The red square shows the artery of interest (with a calcification) at the center. Nearby it is possible to see the jugular vein. **Center**: Initial presegmentation using the statistical analysis values, **Right**: Refined segmentation of lumen.

Presegmentation

An initial rough segmentation uses global thresholds, in order to create the following classes: bone/calcification, lumen, possible lumen (voxels typically belonging to borders that cannot be clearly classified into one category) and other tissues. The values of the thresholds were determined empirically and depend on whether the arteries contain low or high level of contrast agent (Table 1). The decision is based on the average density of the seed points and of their 26 neighbors, compared to an empirical threshold $T = 330$ HU.

Table 1: Threshold values used to classify image components (in Hounsfield Units)

Type of image	**Other structures**	**Possible lumen**	**Lumen**	**Calcifications**
Low contrast	< 50	50-260	261-500	> 500
High contrast	< 330	330-440	441-680	> 680

After this stage only "other tissues" regions are eliminated, while the remaining regions are refined by use of a Fuzzy C-means algorithm, in order to identify only lumen components. The classifier operates over the original image masked by the presegmentation result. The use of 4 different clusters (background, lumen and two classes for calcifications/bones) showed to be enough to approximately differentiate lumen from other tissue types. The resulting mask $M(\mathbf{x})$ is constructed by assigning the value 1 to the voxels classified as lumen, and 0 to the remaining ones (Figure 2).

Enhancement filtering

Density-based image segmentation is often not reliable enough, owing to the vicinity of structures having similar intensities (i.e. the jugular vein). To overcome this, we propose to modify the values of the presegmented regions labeled as lumen, by use of the normalized gradient magnitude $|\nabla I(\mathbf{x})|$. This is done by multiplying $M(\mathbf{x})$ by $1 - |\nabla I(\mathbf{x})|$, which is expected to produce values close to 1 near arteries center and lower values at the arterial boundaries (Fig. 3). To strengthen the response we use an exponential function:

$$V(\mathbf{x}) = \exp\left(k * M(\mathbf{x}) * (1 - |\nabla I(\mathbf{x})|)\right) \tag{1}$$

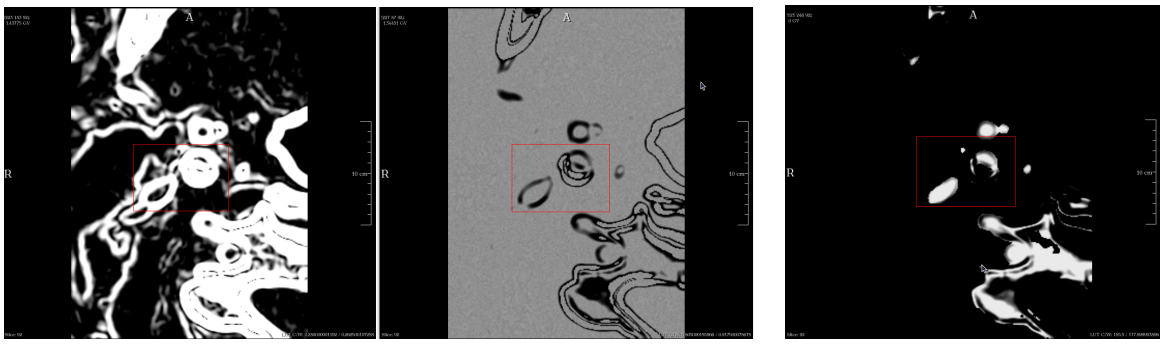

Figure 3: **Left**: Gradient magnitude $|\nabla I(\mathbf{x})|$, **Center**: $1-|\nabla I(\mathbf{x})|$, **Right**: Enhanced image

were k is a tuning parameter that controls the strength of the filter ($k = 0.3$) and $V(\mathbf{x})$ is the filter response. The original image is finally multiplied by $V(\mathbf{x})$ (Fig. 3).

2 Model-based refinement and quantification

Since medical images can contain low-contrast regions where it is difficult to segment using only image intensities, we include a cylindrical artery model that is used for centerline extraction and posterior stenosis quantification. The model represents a centerline by a curve having limited elasticity and flexibility, and passing by or near the local centroids. It also characterizes the cylinder local radius via the eigen-analysis of the inertia matrix. The centerline algorithm extracts the centerline of a vessel, starting from one point within its lumen. It includes the following steps:

a) estimation (refinement) of the current point location, based on centroid information and restricted by continuity and smoothness constraints,
b) estimation of the local orientation of the vessel, based on inertia matrix eigenvectors,
c) prediction of the next (candidate) point, based on the estimated location and orientation.

First- and second-order image moments used in the algorithm are computed within a spherical sub-volume called analysis cell. We use a multi-scale framework to determine the locally most suitable size of the cell. The iterative tracking process is carried out starting from a seed-point, and stops when a boundary of the volume of interest (VOI) or another seed-point is encountered. More details can be found in our previous publications [3, 2].

Centerlines extraction using an elastic model and inertia moments

The tracking process is carried out within the enhanced image. The VOI is created using reasonable margins around the three seed-points provided with the datasets. Since the centerline extraction starts with a single point, three different centerlines are generated: one per seed-point. In order to overcome the missegmentations of structure ”stuck” to the arteries of interest, which can occur at the presegmentation stage, we sweep a sphere all along the carotid centerlines to ”clean up” structures that do not belong to the artery. We use the analysis cell for this purpose. The cell radius corresponds to an estimation of the vessel radius, so it is possible to say that voxels outside the cell radius do not belong to the artery and can be rejected.

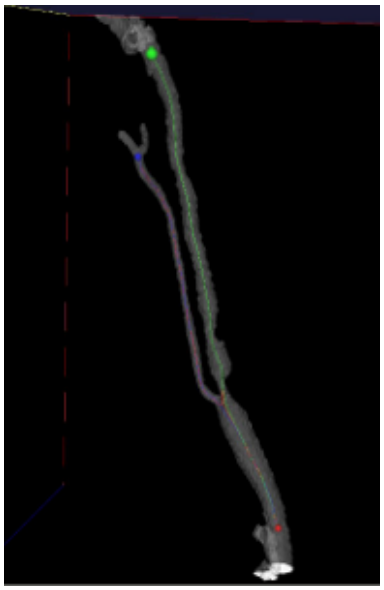

Figure 4: Resulting segmented vessel after including the cylindrical model.

Bifurcation detection and cross-sectional quantification

Bifurcation detection is based on the three previously extracted centerlines. Typically, the three axes must have a common section and at least one of them diverges from the rest at a certain point. Detection of this point identifies the bifurcation.

Since we cannot control, towards which endpoint a centerline heads during its growth, our first step consists in detecting the two lines that diverge the most (to guarantee that they follow the internal and external carotid artery, respectively). For every possible pair of axes we evaluate, on a point-to-point basis, how different they are. The sum of all distances gives a score. The pair of lines giving the highest score is selected to be evaluated. Using the point-to-point distance we detect the region where the distance between the lines is above a given threshold. This point is defined to be the bifurcation. Quantification analysis is restricted to the zone starting from the bifurcation up to the point identifying the internal carotid artery. Using the line along this region and the segmented image, planes perpendicular to the axis are extracted.

Stenosis quantification is performed on a plane-by-plane basis. For every extracted plane, the lumen boundary is extracted by use of isocontours. We compute the area inside the contour as well as minimum diameter.

Once the areas and diameters are computed, every plane is analyzed in order to detect the slice where the smallest area and diameter are found. Once the smallest value is found, the distal plane located 2 cm away (in the internal carotid point direction) is marked as the healthy region. Using this two planes the stenosis is computed following the challenge definition.

3 Results

Both lumen segmentation and stenosis quantification were evaluated on 31 carotid CTA datasets provided by the organizers of the Carotid Bifurcation Algorithm Evaluation Framework. Details of the evaluation methodology can be found on the web page of the challenge (http://cls2009.bigr.nl/).

Table 2: Summary lumen

Measure	% / mm			rank		
	min.	max.	avg.	min.	max.	avg.
L_dice	63.4%	92.6%	80.4%	4	4	4.00
L_msd	0.34mm	2.56mm	0.86mm	4	4	4.00
L_rmssd	0.54mm	4.57mm	1.57mm	4	4	4.00
L_max	1.31mm	11.26mm	6.10mm	4	4	4.00
Total (lumen)				**4**	**4**	**4.00**

Table 3: Averages lumen

Team name	Total success	dice		msd		rmssd		max		Total rank
		%	rank	mm	rank	mm	rank	mm	rank	
Our method	31	80.4	4.0	0.86	4.0	1.57	4.0	6.10	4.0	4.0
ObserverA	31	95.4	1.5	0.10	1.5	0.13	1.6	0.56	1.9	1.6
ObserverB	31	94.8	2.4	0.11	2.4	0.15	2.3	0.59	1.8	2.2
ObserverC	31	94.7	2.2	0.11	2.1	0.15	2.1	0.71	2.3	2.2

Concerning the segmentation, four aspects were evaluated: Dice similarity index, mean surface distance, RMS surface distance and maximal surface distance. The obtained results are presented in Tables 2 and 3.

Stenosis grading was performed using both vessel area and diameter. Quality of the quantification was evaluated by calculating the difference between the quantified value and the one provided by the reference standard. The obtained results are presented in Tables 4 and 5.

4 Discussion

We presented an approach for carotid lumen segmentation and stenosis quantification from CTA datasets. The method is based on a model initially designed for the purpose of vessel segmentation in magnetic resonance angiography images (MARACAS). Our efforts were mainly directed towards the adaptation of MARACAS to segment CTA data and to cope with bifurcations. These adaptations include a three-stage enhancement filter based on image intensities and gradients. While the results were encouraging on training data, the method performed much worse on the testing data. One explanation is that in some of these datasets the seed-point corresponding to the internal carotid was located very low. In consequence, the extracted centerline was too short and the subsequent segmentation and quantification steps partly failed. Nevertheless, other reasons of the counter-performance can be attributed to the method itself. On the one hand, it provides only hard segmentations (0 or 1) instead of including partial volume at the borders. On the other hand, the enhancement filter only based on intensities and gradient magnitudes seems to be insufficient in some configurations. It probably should include local orientations, too.

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Table 4: Summary stenosis

Measure	%			rank		
	min.	max.	avg.	min.	max.	avg.
S_area	0.0%	50.0%	14.3%	1	4	2.94
S_diam	0.0%	56.0%	14.4%	1	4	2.71
Total (stenosis)				**1**	**4**	**2.82**

Table 5: Averages stenosis

Team name	Total success	area		diam		Total rank
		%	rank	%	rank	
Our method	31	14.32	2.9	14.39	2.7	2.8
ObserverA	31	2.71	1.3	3.61	1.6	1.4
ObserverB	31	4.55	1.7	5.29	1.9	1.8
ObserverC	31	5.61	2.3	5.74	2.1	2.2

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