Vessel Segmentation and Stenosis Quantification from Coronary X-Ray Angiograms

Irina Andra Tache[1(✉)] and Dimitrios Glotsos[2]

[1] University Politehnica of Bucharest, Bucharest, Romania
irina.tache@acse.pub.ro
[2] University of West Attica, Athens, Greece

Abstract. Angiography is the gold standard for diagnosis and interventional treatment of vascular pathologies, especially for stenosis, in many hospitals around the world. Still, the physicians complain of visual burdens due to its rather low spatial resolution and artefacts. Fluoroscopic angiography series from the dataset are obtained with standard clinical protocol. In the following, there is proposed an algorithm for vessel segmentation and edge detection. It is related to gradient operator applied on a pre-processed image with the Frangi's vesselness filtering for removing the equipment acquisition noises, followed by morphological operations for removing the spurs and adaptive threholding. The contour tracking along the vessel is done using Dijkstra's smallest path algorithm. The severity of the stenosis for a vessel segment can be assessed visually by a medical imagistic expert. The angiograph software can provide a graphic containing on the X axis the vessel segment length and on Y axis its corresponding cross-sectional areas. More objectively, the percentage of area stenosis can be computed.

Keywords: Vesselness filtering · Vessel pathology · Contour tracking

1 Introduction

The vascular diseases are reflected by problems in transporting the blood into the vessels, also called hemodynamic disorders. The medical imaging is an indispensable procedure in the diagnosis and treatment evaluation of these diseases.

Medical imaging techniques used in the examination of the cardiovascular diseases are: ultrasound investigations, computed tomography, magnetic resonance techniques, angiography, nuclear imaging, scintigraphy and positron emission tomography.

The X-ray angiography or conventional coronary angiography (CCA) is based on the projectional radiography and it is a clinical method for geometry assessment and filling properties of the blood vessels. They are particularly useful in detecting the aneurysms or any interruption of the blood flow through a main branch or the dilation or constriction of the large and medium vessels. Although, the small ones, which have low contrast, are difficult to be examined.

The edge detection is an important image processing step which can be included into segmentation. It is defined as the linear characteristic of the object which has at least one

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neighbour outside the object. Actually, it implies the detection of the discontinuities in the grey levels.

In the scientific literature there are many methods to do vessels' segmentation. Considering that the X-ray angiograms are perturbed by noises with Poisson distributions, the algorithms suitable for on this kind of images are a few. In principal, they consider pre-processing the image before starting the image segmentation.

A review of vessels segmentation and tracking algorithms is presented in [1] and a review for coronary segmentation methods can be found in [2]. A new approach which uses classical image processing tools, such as multiscale adaptive Hessian-based enhancement method and the statistical region merging technique is detailed in [3].

The quantitative coronary arteriography is a tool used by the cardiologist to estimate the stenosis and includes the calibration, automatic contour detection and quantification of stenosis severity. In [4] they use the percent stenosis index which consists in comparing the normal regions and the ones with stenosis for in vivo data acquisition, with a catheter, using videodensity method. In [5] a system and associate methods to quantify stenosis by the percent of area stenosis which starts with the vessel centreline detection from the cardiac Computer Tomography Angiography (CTA) are presented. In [6] they use level sets for CTA segmentation and the so-called NASCET criterion for stenosis quantification which is based on diameters. Also in [7] they use the so-called cross sectional area measurement that takes into account the partial volume effect. In [8] an algorithm for stenosis identification for online 3D data set from CTA which is publicly available in [9].

Other interesting algorithms are related to blood flow estimation from CCA using densitometric measurements (the grey levels values). In [10] they assess the flow which is used for the assessment of the stenosis probability and in [11] arterial flow is computed for digital subtraction angiography.

Two commercial software packages used on the clinical X-ray angiographs are compered and analyzed in [12]. The focus is the performance of the algorithms regarding the accurate detection of stenosis on bifurcation vessels.

The aim of the study is to segment the vascular structures from angiography using simple and fast image processing algorithms and to quantify the coronary stenosis vessel on X-ray angiograms which in medical literature can be found as quantitative coronary angiography (QCA). This can be done by using an algorithm implemented in Matlab® with good performances for vessels contour detection and graphical representation of the cross-sectional areas along the vessel's length. This result can be used by a medical expert to assess the severity of the stenosis, either visually or quantitatively.

2 Methodology

2.1 Data Acquisition

The bones and the calcified plaques are strongly radio-opaque, while the low density elements are hardly visible on radiographs. Therefore, in order to make the opacification of the vessels, an iodine based substance is injected into the circulation.

On the first 3–4 acquired images there are no vessels displayed and as the contrast agent is mixing with the blood, they become to be visible on the image detector.

The image set is comprising data taken from one healthy person with non-significant vessel lesions and data from 10 patients with complete or partial stenosis on the main vessels. The data acquisition characteristics can be found in the Table 1.

Table 1. Protocol and image characteristics

Parameters	Cardiac
Injection site	Main left/right coronary
Projection types	Left and right caudal projection, right oblique anterior projection and left and right cranial projection
Spatial resolution	512 * 512
Contrast resolution	8 bits

2.2 Vessel Segmentation and Edge Detection

Segmentation algorithms for grayscale images are related to the discontinuity and similarity properties of the pixel values. For vascular network segmentation, there are filter enhancement algorithms, morphological operations, vessel tracking methods or classifier based methods. Some simple and quick algorithms for contour detection examine the magnitude of the spatial gradient, or the second order spatial derivative called Laplacian operation. There are also other algorithms such as, Sobel, Canny, Prewitt, etc. which use the spatial convolution masks for pixel by pixel passing.

The Sobel's method exploits the assumption that an edge is found in the maximal image gradient, whereas another method firstly filters the image with the Laplacian of the Gaussian filter and secondly searches the zero crossings. The Laplacian of an image J(x, y) is computed as in [13]:

$$\nabla^2 J(x, y) = \frac{\partial^2 J}{\partial x^2} + \frac{\partial^2 J}{\partial y^2} \tag{1}$$

Canny in [14] proposed a method for the image gradient computation in the neighbourhood pixels and its steps are presented in the followings. The Gaussian filtered image which is a slightly blurred version of the original image is computed. Two Sobel operators can approximate the image gradient and a searching for the local maximum admitted by the output magnitudes in the gradient direction is performed. For limiting the multiple maximum detections due to the existing noises, a hysteresis thresholding is applied for detecting only the strong edges and their low connected branches using the direction information. This algorithm is more robust to noises and can detect the low contrast edges.

An improvement of this filter for optimal edge detector is made by Deriche in [15]. Still, it has not good reviews for noise removal and localization, therefore Kumar et al. in [16] proposed a method for edge detection which implies a median filtering and histogram equalization instead of Canny algorithm.

The median filter is attended to eliminate the intensity spikes by not affecting the edges and the uniformization of the values is made by a histogram equalization which stretches and compresses the image for extracting the edges of the blood vessels. For the vesselness filtered angiograms, the Canny method performed well. An algorithm for the extraction of a vessel's segment borders is proposed:

1. The image is enhanced with Frangi's vesselness filter,
2. On the maximum magnitude image resulted from the step 1 it's applied a region growing algorithm for segmentation,
3. Some morphological operations are applied for removing the spurs and unwanted pixels,
4. On the binary image obtained at the previous step, the user draws two lines for delimitating the segment,
5. For contour detection, the Canny edge detection algorithm is applied,
6. A series of perpendicular lines on the edges are drawn in the vicinity of delimitating lines in order to find two valid intersections with the vessel borders. The closest line which respects this requirement is selected and its points are marked on the binary image,
7. The image from the step 6 is cropped for focussing the vessel segment,
8. The Dijkstra's algorithm is applied for finding the optimal path on one vessel border,
9. The other border is found at the intersection of the perpendicular lines starting from the first detected edge with the binary image obtained at the step 7,
10. Finally, the radius or the cross sectional areas of the segment can be computed.

A visual representation of the workflow is presented in the Fig. 1.

2.3 Quantitative Coronary Arteriography

The quantitative coronary arteriography with the acronym QCA is a standard used by the cardiology physician to assess the coronary artery dimensions [17]. The QCA can help the clinicians in the selection of the optimal balloon and stent. It's an analysis for single or bifurcation vessels.

After the algorithm implementation for automatic contour detection with the vesselness filtering approach presented in the previous section, the length of the vessel segment suspected to include a stenosis is detected with its corresponding cross-sectional areas. With these quantities a graphical representation of the 2D QCA is performed as in the Sect. 3.2 and the severity of the stenosis is judged by an abrupt change of areas. For a more objective perspective, the parameter which characterize the stenosis severity – the percentage of area stenosis (PAS) is introduced using the below equation:

$$PAS(\%) = \frac{A_{max} - A_{min}}{A_{max}} \cdot 100 \tag{4}$$

Where A_{max} is the maximum cross sectional area and A_{min} is the minimal cross sectional area.

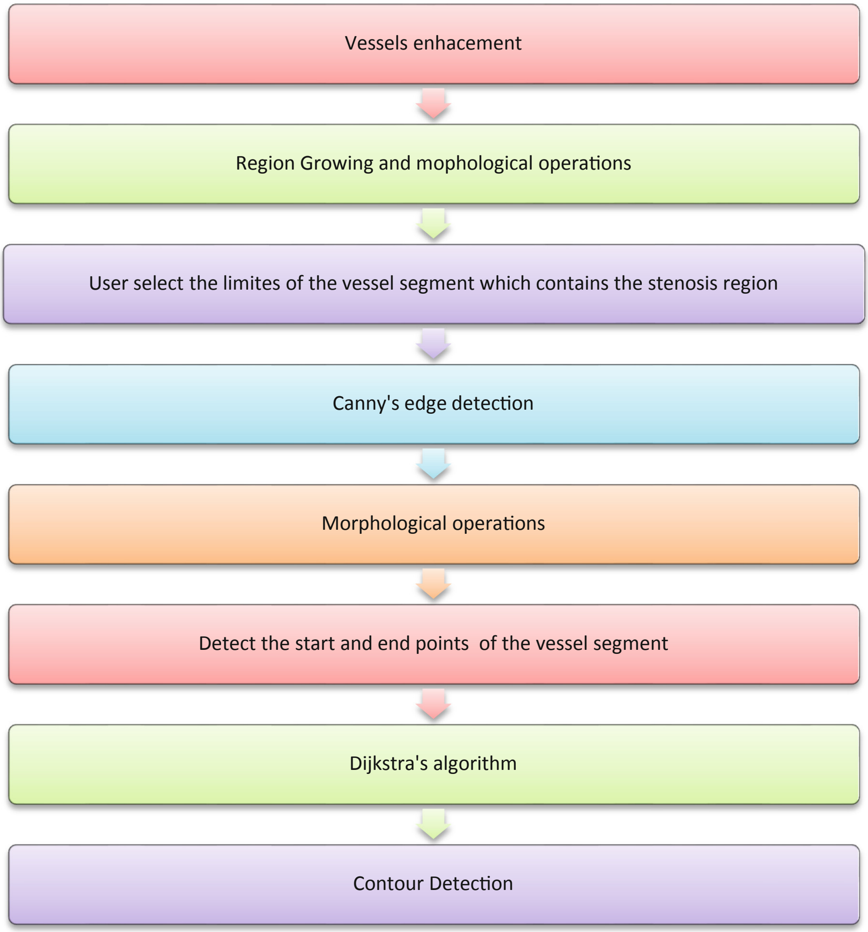

Fig. 1. The steps for automatically extraction of the vessels' contours

3 Results

3.1 Contour Detection

The proposed method is using the Frangi vesselness filtering in order to detect the pixels which are the best candidates to represent a vessel. Based on the maximum magnitude image, a graph is constructed considering the nodes as the image coordinates where the probability of vessel occurrence is high. After defining the start and end points, the shortest paths are then found by the Dijkstra's algorithm (Figs. 2 and 3).

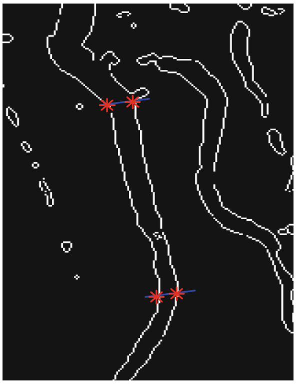

Fig. 2. Vessel's segment identification from ROIs

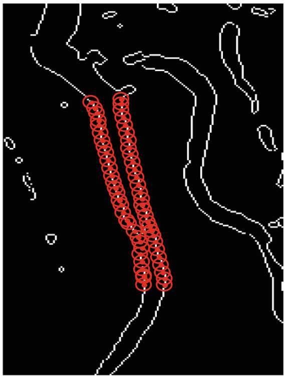

Fig. 3. Vessel's border tracking

The utility of this automatic method is specially dedicated to abnormal tubular structures which will further permit the computation of the stenosis geometrical angiographic quantification. Still, for the severe cases it can fail, due to the interruption in the vessel edge continuity.

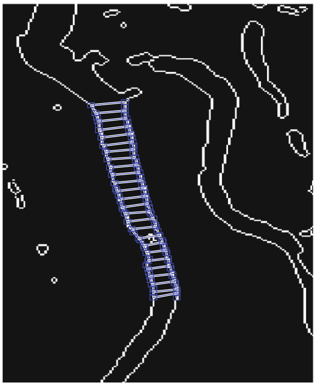

Fig. 4. Vessel's radius

3.2 Stenosis Quantification

On the results obtained in the Fig. 4 the further analysis is focussed on the small vessel narrowing. After the contour detection, a graphical representation of the cross-sectional areas along its length from a projectional view is presented in the Fig. 5(a).

In Fig. 5 it can be observed the differences between a non-significant and a severe stenosis. For validating the method, the resulted QCA graphical representation is compared with the one from the medical equipment which was previously approved by a

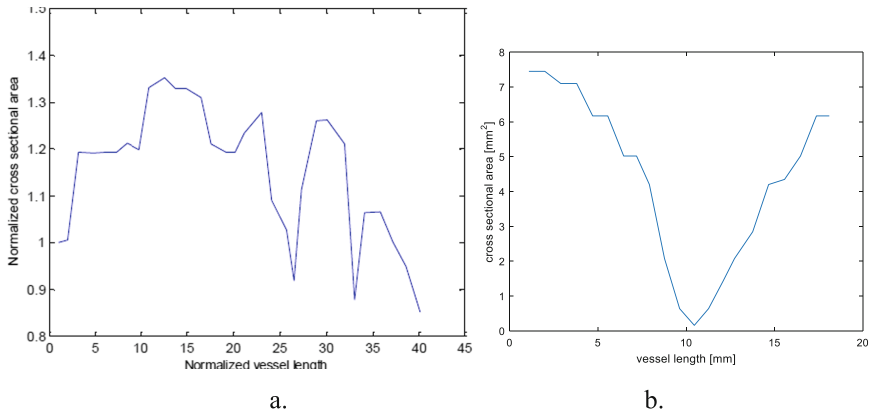

Fig. 5. The QCA graphical representation (a) for an insignificant stenosis (b) for a severe stenosis

physician. Also because the physician diagnosed the vessel obstruction from the Fig. 5(b) as complete stenosis, hence the percentage of area stenosis will expect to be almost 100% after the physician visual inspection. As can be seen from the graphic A_{max} is 7.5 mm^2 and A_{min} is 0.2 mm^2, which means that the PAS parameter is 97.33%. The results are consistent from these two reports.

4 Conclusions

The key step in improving the medical images for a quick diagnostic is the segmentation process which can be regarded as pixels' classification into two groups: the object and the background. This step is necessary for centreline and contour detection of the vessels. This target is not properly achieved if the noise is not correctly filtered in the original image.

The method works well in some cases and the vessel sizes can be computed but the performance degrades when there is background clutter in the angiogram, such as spines, catheters, and guidewires. Furthermore, vessel crossings could be incorrectly identified as vessel bifurcations.

This image processing algorithm is further used for geometrical quantification of the vessels (radius, cross-section areas and vessel's length) and for quantification the stenosis severity using the QCA tool.

Further work may include the refinement of the vessel structure extracted from a 2D angiogram by using prior shape information from a 3D coronary vessel model of the same patient. For the edge detection the gradient approach is used after the Frangi vesselness filtering followed by some morphological operations. The method is automatic and it's suitable for a wide range of vessels.

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