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Title: Advances in quantitative coronary and vascular angiography
Date: 2012-10-11

CHAPTER 2

Inventory Contour Detection Algorithms

2.1 Introduction

Quantitative coronary arteriography (QCA) has been widely used for the detection and accurate assessment of the morphology of coronary vessels and the localization and measurement of obstructions from X-ray arteriograms. The accurate derivation of clinical parameters such as obstruction diameter and percentage diameter stenosis has proven to be very useful in clinical trials as well as in online applications in interventional cardiology.

In spite of the high accuracy and precision that has been shown by several packages [49, 36, 50, 51, 52] and the increasing complexity in cardiovascular interventions, the use of QCA and QVA (Quantitative Vascular Analysis) tools is still limited because of the manual interactions and corrections that are needed in routine clinical practice, and therefore the majority of the angiograms is still visually interpreted. This is obviously not the case in clinical trials, which are almost exclusively analyzed by the QCA approach, and which allow more time for the analysis. Currently there is still insufficient motivation by the interventional cardiologists to use QCA during the procedure, despite the fact that it may result in cost savings, better prognosis for the patient, etc; this will change if the insurance companies and the hospitals themselves are going to demand a quantitative proof of the need for the intervention and for the number and types of stents to be used, that is evidence based medicine. It may also change if the procedures become so complicated that absolute vessel sizes are needed to obtain acceptable results, such as in the case of complex bifurcation stenting.

A substantial part of the research that has been done for the current QCA packages focused on the automated detection of the borders of the vessel in order to achieve a robust and reproducible measurement. Nevertheless there are some difficulties that still have to be overcome in order to achieve a robust tool that works with all kind of images in a reproducible way. For example there is always a trade-off that has to be made between the smoothness of the contour and the ability to detect complex lesions. A smooth contour is more robust with respect to noise but cannot follow complex stenoses, whereas a contour with more freedom can detect the irregular lesions but also tends to be influenced by the noise in the image.

In this chapter, an overview will be given of the work that has been done in the field of contour detection approaches for QCA applications, which will point out the advantages and disadvantages of these approaches.

2.2 Methods

In general, several mathematical algorithms have been commonly used for contour detection purposes, and a number of them have already been tried for QCA applications. The algorithms are grouped by category and discussed below.

2.2.1 Thresholding

One of the most straight-forward approaches is a simple thresholding or region growing. These approaches have proven to be not very suitable for contour detection in vascular X-ray angiograms since they are quite coarse, (no sub-pixel accuracy) and require a fixed threshold as input, which is very difficult or even impossible to choose in X-ray images.

2.2.2 Edge detection and grouping

A large category of contour detection algorithms is based on the principle of edge detection and grouping of the candidate edge points. A number of these approaches are used widely in the QCA field and are discussed below.

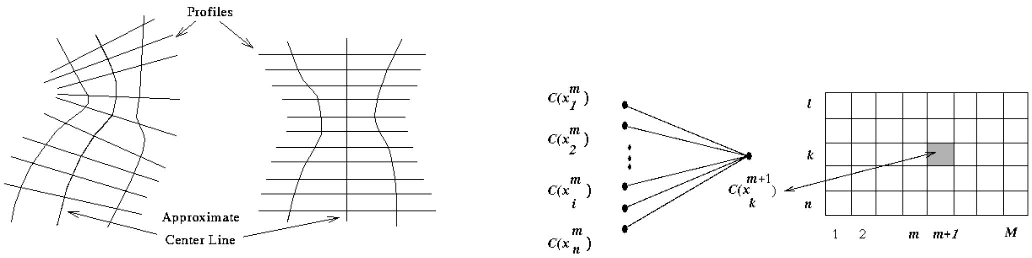
Minimal Cost Algorithm (MCA)

This contour detection method consists of a derivative approach in combination with dynamic programming. This approach is present in the existing version of the QAngioXA package. The basic derivative approaches are based mainly on a combination of the first and the second derivative of the image intensity function [53, 54, 55, 56]. Edge-points can be localized by finding the extrema of the first order derivative or by finding the maxima of the second order derivative. Due to uncertainty in the images, for example due to the noise of the imaging system or the unknown shape and orientation of the vessel, the first order derivative tends to find edges inside the vessel, whereas the second order derivative is more likely to find edges outside the vessel area. In order to correct for these systematic errors, a weighted average of the localization using the first and second order derivatives is calculated to give the best estimation of the edge localization. Nevertheless, tuning the algorithm by finding the optimal weights is certainly not trivial and the approach is still quite sensitive to the noise in the image [57].

In the MCA method, this problem of uncertainty in edge location and direction is solved by the dynamic programming technique [54, 55, 56]. This approach mainly consists of using an estimate of the vessel's centerline to construct scanlines perpendicular to it. Along the scanlines the image is resampled into a matrix in which the weighted sum of the first and second order derivatives determines the local cost. The dynamic programming technique minimizes the costs of a path through the matrix. This minimum cost path is warped back onto the image as the resulting contour. This approach that will result in a continuous path, will work well under the condition that it is a normal vessel whose contours are relatively smooth, see Fig. 2.1. The overall accuracy that can be achieved is 0.001 mm and the overall precision in this case is 0.096 mm, measured with plexiglass phantoms of varying diameter. On the other hand, applying this technique to a complex lesion leads to incorrect contours because of the continuity of the algorithm and the fact that intercepting scanlines in sharp corners can cause incorrect contours, because the undersampling on the outside can miss edges and the oversampling on the inside can produce misleading edges.

Furthermore the results of the algorithm depend strongly on the positions of the start- and endpoints that are defined by the user, since not only the position of the pathline, but also its length determines the positioning of the scanlines and therefore the resampling of the image. Therefore, the contours cannot be found in a totally reproducible way.

Another problem that occurs using this approach is the overestimation of the diameter of small vessels. A postprocessing method is needed to correct for this imperfection, but this does not take into account the different edge profiles that are present at small vessel boundaries compared to the ones at large vessel boundaries [58, 59, 60]. When the correct edge profile had been taken into account, the boundary of these small vessels would be found with higher accuracy.



(a) (b)

Figure 2.1: MinCost Algorithm: a) Resampling and b) Dynamic Programming

Finally, the approach is solely based on edge information and does not take the grey value itself into account. This means that the algorithm does not have knowledge about the intensity in the background, which can cause the algorithm to lock onto the wrong contour, for example the catheter inside the vessel.

Gradient Field Transform

As improvement of the mincost approach, the Gradient Field Transform (GFT) was developed [54, 50] as well as the Sequential Edge Detection (SED) algorithm [56]. These algorithms are based on the same approach, i.e. a detected centerline is used to determine scanlines along which the image is resampled. In this matrix the possible derivative based edge points are given cost values associated with the edge strength as well as the edge direction, see Fig. 2.2. Minimum cost approaches are subsequently used to find a path through the possible edge points which results in the initial edges. Next, these edges are used to achieve a better approximation of the vessel centerline which is very important in order to achieve a finer edge determination.

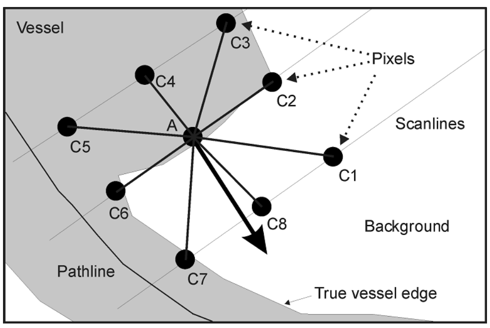


Figure 2.2: The principles of the GFT (figure from Zwet et al. [54])

Using the same plexiglass phantoms of varying diameter, the overall accuracy was found to be 0.004 mm and the overall precision 0.114 mm. The advantage of this algorithm over the previously discussed mincost approach, is that the directional information of the edges is taken into account in the cost function which leads to a more accurate determination of the edge location. Furthermore, the algorithms are not restricted to only one single edge point on each scanline, which results in an ability to follow more complex lesion morphology.

However, the model that is used for the detection of the initial edges has a big influence on the detected contours. In case of irregular lesions, the model has to be smoothed heavily and resampled uniformly in order for the scanlines not to intersect. This causes the approach to perform worse in case of sharp edges and the calculation of the vessel diameter will be less accurate.

Just as the mincost algorithm, this approach also depends strongly on the position of the start- and endpoint. Therefore, the contours cannot be found in a very reproducible way, when analyzing an image repetitively. The problem of overestimation of the diameter of small vessels that is present using the mincost approach is also a part of this approach, since the edge profile is not adjusted for the diameter of the vessel. To improve the performance of these above mentioned edge detection based methods, the matched filters estimations have been developed. Van der Zwet and Nettesheim described a method to derive an optimal filter to detect the edges of coronary arteries [60]. This method takes into account the point-spread function of the cardiovascular X-ray system and derives an optimal filter to detect the edge profile, associated with the given diameter. It shows that the systematic errors are close to zero and the standard deviation is in the order of 0.02 mm. Similar research has been carried out by Jalali et al. [61] where they try to find an approximation of the edge profile (in this case without additional knowledge about the transfer function of the imaging system) and derive an optimal filter to detect the estimated edge-profile. Miles et al. [59] derive a matched filter assuming that the vessel has a blurred half elliptical profile.

One problem with this approach is that the edge profile is not antisymmetric (as assumed by Petrou [62], an extended version of Canny's edge detector [63]) and thus the profile of the optimal detector is not symmetric. This implies that it is not simple to extend the 1-dimensional profile to a 2-dimensional one. This is a problem that has to be solved in order to get rid of the scanlines and use edge detectors that can detect edges in any orientation.

Morphological Filtering

Another approach, that still uses the principle of edge detection and grouping, is the morphological filtering [64]. This approach is quite similar to the mincost approach in the sense that it uses image resampling and dynamic programming techniques to obtain the vessel contours. The difference is that the cost function is now determined by morphological instead of derivative based edge detection operators, for example grey value erosions and dilations.

A number of limitations characterize this approach. The analyzed segment should not contain bifurcations, no other vessels should be in the neighborhood and since the scanlines should be perpendicular to the vessel, it has to be more or less straight. The algorithm does not take into account the width and the orientation of the vessel, which generally leads to inferior results.

2.2.3 Model-based

Another category of algorithms are the model-based approaches. These methods try to make a model of the total imaging system, background, arteries, noise [57]. This is matched to the image intensities and the parameters of the model are estimated using a mean square error method. This method needs a joint optimization process for the combination of parameters, which are subsequently used for the estimation of the vessel statistics. This method has a few disadvantages, such as the simplicity of the model that is used, the processing time of the algorithm and the dependency on the detected vessel centerline. Moreover, in case of a stenosis in the vessel that may perpendicularly align with the centerline, more than one edgepoint may exist, which cannot be detected by this approach.

2.2.4 Active contours

Active contours (snakes) [65, 66, 67, 68, 69] form another group of contour detection algorithms that have been used for the detection of vessel borders. Snakes are parametric curves that deform under the influence of internal and external forces to find the object contour. The internal forces are a measure for the degree of deformation of the spline, whereas the external forces are determined usually by some kind of edge detection method. Klein et al. used a deformable spline model to detect the coronary artery borders [70, 71]. In small diameter measurements, an accuracy of -0.19 pixels and a precision of 0.53 pixels were obtained.

A big advantage of this method is its ability to create a smooth, continuous contour, even through areas where there is very little edge information, for example at the position of a side-branch. However, this ability also results is difficulties when trying to follow complex lesions. The smoothness of the model will cause the algorithm to underestimate the severity of very short stenoses simply because it cannot make a sharp turn. The initialization of the model can have a big influence on the final result of the segmentation. The minimum that is found by the algorithm is not necessarily the global minimum.

As an improvement to the regular snake algorithm, a new approach was developed, the gradient vector flow snake, that uses a gradient vector field (GVF) as external force for the active contour model [72, 73]. This approach is less sensitive to the initialization. It is designed to find the global maximum in all situations and not to stop in a local maximum. Furthermore, this type of snake is able to follow strange morphological structures such as convex curves which is virtually impossible with a regular snake. A disadvantage of using this method is that a closed contour must be produced and that the algorithm cannot adjust the edge profile according to the diameter of the vessel since the vector field is already made before the model is matched onto the image. This algorithm has been tested, but never validated for vascular images.

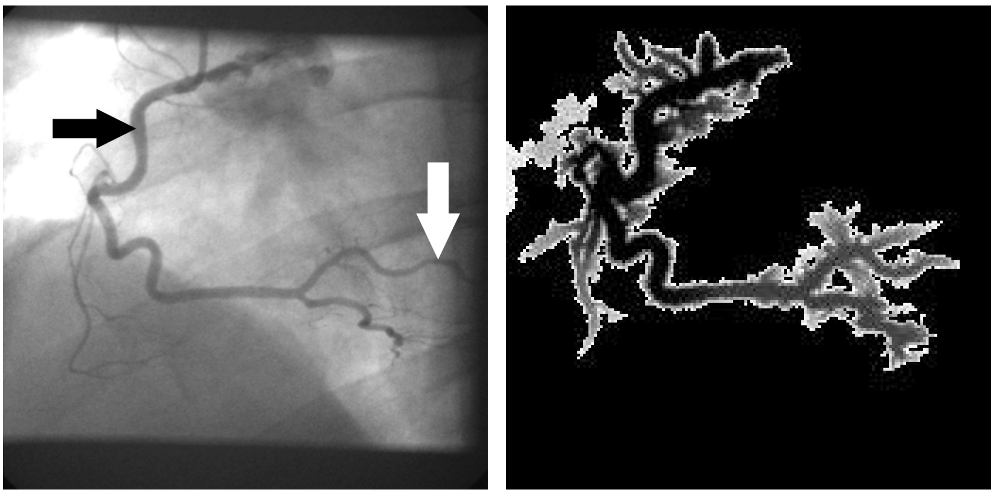
Another extension to the normal active contour models is the Topology adaptive snake, T-snake [74]. The advantage of this approach over the regular snake models is its ability to change topology. The snake can split into two parts, join another snake, create a hole and so on. It may be used for an initialization with multiple pieces (one piece around the startpoint and one around the endpoint, for example). However, this freedom can also cause the algorithm to find non-continuous contours.

Another approach, an attractable snake that is based on the greedy algorithm for contour extraction [75] has been designed to make the active contour model more robust. An overall optimal edge detector is used to avoid local minima and to make the approach less dependent on the initialization. An adaptive interpolation scheme is used to sense the details of object shapes, also convex shapes. This approach also requires the definition of an edge profile before the algorithm starts, which makes it impossible to adjust this profile according to the estimated diameter of a vessel.

2.2.5 Level set

Another type of algorithms is the level set based approaches. Level sets are geometric models that can segment an image into regions with smooth interiors [76, 77, 78, 79]. The computation of level sets however is generally a costly operation and it remains difficult to achieve consistent boundaries in noisy images because it is not bound to a certain topology. The fastmarching level set segmentation, also called wavefront propagation [80, 81], is a very fast method to calculate the position of monotonically advancing fronts. This method initiates a wavefront in the image and progresses with a speed dependent on the grey-value of the pixels. When it is stopped at the correct moment, a segmentation of the vessel segment [82, 83] can be obtained by taking the envelope of the area that the wave has reached as the resulted contours.

Since the algorithm is very robust and does not depend on scanlines and image resampling, the detected contours are stable and robust. The problem of under- and oversampling in sharp corners is eliminated since no scanlines are used. The algorithm is able to follow structures with a complex morphology and also global structures with the use of the different parameters. However, the issue of when to stop the algorithm, which is the most important part of the segmentation, is not trivial (see Fig. 2.3). This may cause an inaccuracy in the detected contours. Furthermore, there is the problem of leaking, when another vessel or background structure is projected on top of the vessel of interest.



(a) (b)

Figure 2.3: Wavefront Propagation: a) Initial image with startpoint (black) and endpoint (white) and b) Resulting image after propagation (figure from Janssen et al. [84])

2.2.6 Watersheds

Very common in image processing is the method that consists of using watersheds [85] to divide the image in separate regions, which coincide with the different objects in the image. Although the watershed transformation is a powerful method, the main problem using this algorithm for edge detection is that it depends strongly on the gradient operator that has been used before applying the watershed transform. The scale of the gradient operator determines the amount of edges that are found and also the size of these edges. Although more research has been performed to solve this problem [86], noise still remains a major problem.

2.2.7 Markov Random Fields

The next method, Markov Random Fields (MRF) [87], is a region-based approach that tries to group pixels whose intensities are statistically similar, making it more robust with respect to localized image noise compared to using the edge-information. However, when there's a strong inhomogeneity present in the contrast filling of the arteries, the MRF has great difficulties separating the foreground from the background and it often results in small holes/islands inside the segmented object.

2.2.8 Graph Cuts

Another technique that is used for segmentation problems nowadays is Graph Cuts [88, 89, 90]. This approach uses graph theory to segment an image into different regions by maximizing the flow through a graph that is representing the image. This is done by defining a source and a sink in the image (foreground and background) and removing the minimal edges, the edges that connect pixels with large differences in intensity. In this way the optimal cut to separate the foreground from the background is found. The results however are strongly dependent on the initialization and the algorithm has difficulties detecting the edges when there is only little contrast in the image.

2.2.9 Statistical models

Other sophisticated algorithms have been developed like Active Shape Models (ASM) and Active Appearance Models (AAM) [91], both statistical models trained from examples and describing the object boundaries in terms of variations to the mean. These algorithms use high-level knowledge about the object to constrain the deformations of the model, which makes them robust for image interpretation. These methods have proven their value in other fields of medical image processing, such as magnetic resonance imaging [92, 93, 94, 95] but are not useful in X-ray applications because of the large variation in images, in vessels shape and in background structures that are present in this field.

2.3 Discussion

In order to become widely applicable in practical use, a QCA contour detection approach must satisfy a number of criteria. The method must be robust towards the selection of start- and endpoints and it must be able to achieve reproducible measurements in the sense that the same contours must be found, when analyzing the same segment repetitively. Also, it must be minimally dependent on the size of the image intensifier that is used. Furthermore it must not suffer from a systematic over- or underestimation, neither for small, nor for large vessels. The approach should have enough freedom to follow complex lesions, but at the same time be smooth enough to be relatively insensitive to the noise in the image and be able to cross side-branches. Finally it must be fast enough for online applications.

Since there can be a large variety in the morphology of the target vessels, as well as in the background, especially in images of peripheral arteries, the model based contour detection techniques are less suitable for the QCA/QVA applications. Most of the commonly used contour detection methods are in the category of "edge detection and grouping", which is understandable since the edge information is the only reliable contour information in the images.

However, the introduction of scanlines for resampling causes variation in the detected contours when the start- and endpoints are shifted only slightly. Furthermore, scanline-based methods suffer from oversampling and undersampling in sharp corners, which can lead to failures in those areas. To avoid these problems, a global filtering method is needed that can detect edges in any direction to identify candidate edge-points and an algorithm that can connect the most probable candidate edge-points forming the resulting contour. For the grouping of these edge-points, the wavefront propagation is a good method to be used, since it has proven its reproducibility and speed in the pathline tracing algorithm 'Wavepath'. When the wavefront propagation is given the edge information as input instead of the grey-value, it is able to follow edges in any direction. However, the requirement for smoothness, for example in order to be able to cross side-branches, requires an additional solution. The accuracy of the detected contours relies mostly on the accuracy of the edge-detection filter that is used. To ensure maximum accuracy, the optimal edge-profile can be used as described by the matched filter from Van der Zwet. This approach computes the optimal filter as a function of the vessel diameter, which causes the need for a two-stage approach, with the first stage a detection of preliminary contours and an initial estimate of the diameter of the vessel, and a second stage to apply the optimal filter and fine-tune the contours.