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A coronary artery segmentation method based on multiscale analysis and region growing

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ABSTRACT

Accurate coronary artery segmentation is a fundamental step in various medical imaging applications such as stenosis detection, 3D reconstruction and cardiac dynamics assessing. In this paper, a multiscale region growing (MSRG) method for coronary artery segmentation in 2D X-ray angiograms is proposed. First, a region growing rule incorporating both vesselness and direction information in a unique way is introduced. Then an iterative multiscale search based on this criterion is performed. Selected points in each step are considered as seeds for the following step. By combining vesselness and direction information in the growing rule, this method is able to avoid blockage caused by low vesselness values in vascular regions, which in turn, yields continuous vessel tree. Performing the process in a multiscale fashion helps to extract thin and peripheral vessels often missed by other segmentation methods. Quantitative evaluation performed on real angiography images shows that the proposed segmentation method identifies about 80% of the total coronary artery tree in relatively easy images and 70% in challenging cases with a mean precision of 82% and outperforms others segmentation methods in terms of sensitivity. The MSRG segmentation method was also implemented with different enhancement filters and it has been shown that the Frangi filter gives better results. The proposed segmentation method has proven to be tailored for coronary artery segmentation. It keeps an acceptable performance when dealing with challenging situations such as noise, stenosis and poor contrast.

1. Introduction

X-ray coronary angiography (XCA) is the gold standard for the assessment of clinically significant coronary artery diseases (CAD) [1]. The angiograms obtained by the XCA enable to reveal the initial CAD symptoms by the morphological features of the coronary arteries such as diameter, length, branching angle, and tortuosity. However, complex vessel structure, image noise, poor contrast and non-uniform illumination make vessel tracking a tedious task. Accurate coronary vessel detection is a fundamental step in various medical imaging applications such as stenosis detection [2], 3D reconstruction [3] and cardiac dynamics assessing [4]. Vessel detection is generally related to two important tasks which are vascular features enhancement and blood vessel segmentation.

The enhancement step aims to improve the vessels delineation while reducing background artifacts. So far, a variety of vessel enhancement methods have been proposed [5–13]. Truc et al. [14] distinguish three method classes: linear filtering [15], non-linear anisotropic filtering [16,17] and Hessian-based multiscale filtering [5–10].

Linear enhancement methods generally use Gaussian kernels or Gabor filters in order to denoise images. They are inappropriate to complex vascular structures since they blur vessel borders as well as thin vessels.

Unlike the linear smoothing filters, non-linear anisotropic diffusion filtering adjusts the filter for local variations by acting mainly along the preferred structure direction [16]. Hence, important features are better preserved during the smoothing process. Those filters are widely applied in many image processing tasks such as fingerprint image filtering [18], optical coherence tomography image denoising [19] and cell membrane enhancement [20]. The main drawback of diffusion based methods is that they usually act at a fixed scale and are therefore unable to detect vessels within a wide range of size.

Most of the research on vessel enhancement falls into Hessian-based methods. These methods utilize the second order derivatives matrix (Hessian matrix) of the image intensity in order to detect tubular-like structures. For that, the Hessian matrix at each pixel

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is computed by convolving the initial image with second-order Gaussian derivatives. Then, the Hessian eigenvalues and/or eigenvectors are often used to propose a vesselness measure which can be interpreted as the probability of belonging to a blood vessel of a pixel. The vesselness generates maximum response at the scale which matches the diameter of the vessel to be detected. The main advantage of methods in this category is that they can perform in a multiscale fashion, thus detecting different sized objects.

In [21], the authors compared four different Hessian-based multiscale filters, namely those proposed by Koller [5], Sato [6], Frangi [7] and the vessel enhancing diffusion (VED) filter [17]. VED is a diffusion filter built upon the Frangi filter. It can be seen as a generalization of anisotropic diffusion to iteratively smooth the image, while preserving the vessel structure [17]. This filter was initially proposed by [22] and extended by Manniesing et al. [17] who added a smoothness constraint and an enhanced diffusion scheme. Results of this study showed that the two latter outperform the others with a better background suppression performance and vascular structure enhancement.

The second important step in vascular analysis is vessel segmentation. Existing segmentation methods can be divided into two general categories [23]: skeleton based, and non-skeleton based. The principle of skeleton-based techniques is the segmentation of vessels by first detecting the centerlines, then estimating the vessel width. A typical problem with this class is that it can fail to approximate the vessel segments which present stenosis and bifurcations. Non-skeleton-based segmentation techniques, on the other hand, are those that extract the vessels directly. Methods in this category vary from thresholding [24–26,3], fuzzy clustering [27], mathematical morphology [28,29,13], deformable models such as active contour and level set [30–33], graph cuts [34–36] to region growing [37–43]. A more general review on vessel segmentation can be found in [44,45].

Region-growing has been widely used for image segmentation [46], and in particular medical image applications such as vessel extraction. The rationale for this popularity is that these methods are based on a connectivity assumption, which is naturally suited to the case of the vascular trees [47,48]. Methods in this class incrementally segment an object by recruiting neighboring pixel starting from seed points or regions located inside a vessel based on some inclusion rule. Defining a robust region growing rule for X-ray vessel segmentation may encounter several difficulties such as image artifacts, lesions, noise and very low contrast between the vessels and the background particularly in thin vessels location. Therefore, classical region growing methods based on grey level values and/or spatial proximity are often sensitive to noise, and inhomogeneous contrast, which often leads to false negative (hole), false positive (leakage) and unwanted stop of region-growing [45].

In coronary artery angiograms, several factors such as image artifacts, stenosis and noise may introduce discontinuities, hence region growing may result in holes and over-segmentation. To avoid such problems, the growing process was performed in many frames of the same sequence in [37]. Although discontinuities may be avoided by temporal tracking, other difficulties such as centerline matching and user interaction in each step are necessary in this approach. Instead of using the intensity feature in the growing process, authors in [49] incorporate the Frangi vesselness filter [7] in order to introduce more seed points when the growing process stops. In [41], the authors proposed a novel vesselness function and performed vessels segmentation in two steps. First, large vessels are extracted from the maximum vesselness response by region growing. However, this final vesselness response given by the maximum response among the scale space may present low values for thin vessels, junctions and stenosis location. Thus, discontinuities may occur if the growing process is applied directly on this final vesselness image. That is why a detail repairing process is launched in order to extract thin vessels using a direction information given by the first directional derivatives i.e. image intensity gradient.

Combining the vesselness function with a directional information for vessel tracking is certainly a good idea but the image gradient is not, in our opinion, the appropriate direction information descriptor. A more precise direction descriptor would be given by the Hessian matrix eigenvectors. This idea was investigated in [50] where the authors combined the Sato vesselness function [6] with the line direction information given by the first Hessian eigenvector to guide the segmentation of 3D blood vessels. As discussed in [21], the Sato filter is more sensitive to noise than the Frangi filter when applied to 2D X-ray angiograms. Fig. 1 shows that background noise is better removed by the Frangi filter than the Sato one.

In this paper, a multiscale vessel segmentation method for X-ray coronary angiography images is presented. This method takes advantages from multiscale Hessian analysis strength and aims to overcome the two major problems encountered in region growing techniques which are the difficulty of detection of poorly enhanced vessel segments and the occurrence of false positives [50]. The major contributions of this paper are three-fold: (1) From methodological point of view, we combine both Hessian geometrical features which are eigenvalues and eigenvectors to define a robust new region growing criterion tailored to the coronary artery segmentation problem. This criterion is integrated into a mulitscale region growing algorithm ensuring the detection of different sized vessels. (2) We propose an evaluation database containing two datasets with different challenging degrees, which allow the quantitative evaluation of the method in terms of region overlap, sensitivity and precision. To the best of our knowledge, there is no standard database available for this task. The only database available in the literature was proposed by [36] and was designed to evaluate centerline extraction methods rather than segmentation evaluation. (3) We evaluate our method from two aspects, which are the enhancement filter and the segmentation methods. The remainder of this paper is organized as follows. In Section 2, background concepts related to our approach are reviewed. Section 3 illustrates the proposed method in detail. Experiments are described in Section 4. Some illustrative results are given in Section 5. Section 6 presents discussion and concluding remarks.

2. Background on multiscale analysis

The idea of multiscale image analysis is to add a new dimension to the analysis which is the image scale. The image is transformed into a set of blurred images, each representing the original image, but at a different scale [51]. These blurred images are obtained by convolving the initial image $I_0(p) = I_0(x, y)$ with a Gaussian kernel to represent the information at a certain scale.

$$I_\sigma(p) = I_\sigma(x, y) = I_0(x, y) \otimes G_\sigma(x, y) \tag{1}$$

where I_σ is an image of the scale space, $p = (x, y)$ is a pixel location, $\otimes$ represents the convolution operation and $G_\sigma(x, y)$ is the 2D Gaussian kernel with standard deviation σ defined as:

$$G_\sigma(p) = G_\sigma(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp -\frac{(x^2 + y^2)}{2\sigma^2} \tag{2}$$

where $\sigma \in \Sigma = \{\sigma_{min}, \ldots, \sigma_{max}\}$, σ_{min} and σ_{max} are set according to the approximate width of the smallest and largest vessel to be detected [51].

In the scale space framework, differentiation is defined as a convolution with derivatives of Gaussian:

$$\left(\frac{\partial^{n1+n2} I}{\partial x^{n1}\partial y^{n2}}\right)_\sigma = I \otimes \frac{\partial^{n1+n2} G_\sigma}{\partial x^{n1}\partial y^{n2}} \tag{3}$$