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IRBM

IRBM 38 (2017) 167–175

TAIMA

Multiscale Graph Cuts Based Method for Coronary Artery Segmentation in Angiograms

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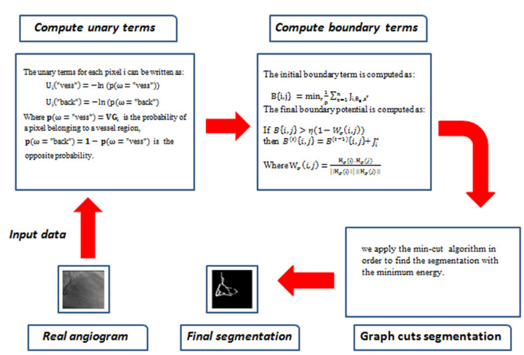
Received 13 September 2016; received in revised form 27 April 2017; accepted 28 April 2017
Available online 15 May 2017

Graphical abstract



Abstract

Context: X-ray angiography is the most used tool by clinician to diagnose the majority of cardiovascular disease and deformations in coronary arteries like stenosis. In most applications involving angiograms interpretation, accurate segmentation is essential to extract the coronary artery tree and thus speed up the medical intervention.

Materials and Methods: In this paper, we propose a multiscale algorithm based on Graph cuts for vessel extraction. The proposed method introduces the direction information into an adapted energy functional combining the vesselness measure, the geodesic path and the edgeness measure. The direction information allows to guide the segmentation along arteries structures and promote the extraction of relevant vessels. In the multiscale analysis, we study two scales adaptation (local and global). In the local approach, the image is divided into regions and scales are selected within a range including the smallest and largest vessel diameters in each region, while the global approach computes these diameters considering the whole image. Experiments are conducted on three datasets DS1, DS2 and DS3, having different characteristics and the proposed method is compared with four other methods namely fuzzy c-means clustering (FC), hysteresis thresholding (HT), region growing (RG) and accurate quantitative coronary artery segmentation (AQCA).

Results: Comparing the two proposed scale adaptation, results show that they give similar precision values on DS1 and DS2 and the local adaptation improve the precision on DS3. Standard quantitative measures were used for algorithms evaluation including Dice Similarity measure (DSM), sensitivity and precision. The proposed method outperforms the four considered methods in terms of DSM and sensitivity. The precision values of the proposed method are slightly lower than the AQCA but it remains higher than the three other methods.

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http://dx.doi.org/10.1016/j.irbm.2017.04.004

Conclusion: The proposed method in this paper allows to automatically segment coronary arteries in angiography images. A multiscale approach is adopted to introduce the direction information in a graph cuts based method in order to guide this method to better detect curvilinear structures. Quantitative evaluation of the method shows promising segmentation results compared to some segmentation methods from the state-of-the-art.

Keywords: Coronary angiography; Segmentation; Graph-cuts; Multiscale analysis

1. Introduction

Cardiovascular diseases have been for decades the leading cause of death, it is therefore crucial to detect as early as possible any deformation in coronary arteries. Classical diagnosis procedure includes the analysis of X-Ray angiography allowing to identify location and severity of arterial diseases, to quantify them and follow-up during treatment or surgery. To assist experts in their diagnosis, segmentation of the coronary arteries is an essential step aiming to eliminate artifacts contained in the background.

A lot of researches have been done on development of methods for blood vessel segmentation. In [1], authors present a standardized evaluation framework to assess the performance of algorithms designed to detect and quantify coronary stenosis and coronary artery lumen in computed tomography angiography (CTA) data.

Developed methods can be divided into two general categories; skeleton and non-skeleton methods [2,3]. The main idea of skeleton-based techniques is to extract blood vessel centerlines first and then create the vessel tree by connecting these centerlines and estimating the vessel width. This centerline structure is commonly used for 3D reconstruction. Toledo et al. [4] proposed a skeleton-based technique using training models for segmenting the coronary vessels in angiograms. This technique used deformable models where the external energy was computed based on training datasets. Tozaki et al. [5] detect lung bronchus and blood vessels from thin slice CT images. Their method starts by applying a threshold to segment the images. Then using anatomical characteristics, blood vessels and bronchus are separated and finally a 3D thinning algorithm is applied to extract the vessels centerlines. Kawata et al. [6] extract blood vessel diseases from cone-beam CT images by first applying a graph description procedure using thresholding, removing small connected components, and finally the characteristics of convex and concave shapes on the surface of blood vessels are extracted using 3D surface representation. Sorantin et al. [7] work on spiral CT images and apply a 3D skeletonization method for the estimation of stenoses.

The principle of non-skeleton category is to directly extract blood vessels based essentially on the pixels intensity. This category can be divided into sub-categories including model based approaches like active contours [8,9] and tracking based techniques that start from an initial point and track the vessel centerline or boundaries by locally analyzing the pixels orthogonal to the tracking direction [10–12]. Non-skeleton methods includes some other pattern recognition based techniques like mathematical morphology [13–15], fuzzy clustering [16] and neural network [17] where authors use a backward propagation network to label image pixels.

Depending on similarity and spatial proximity criteria, the authors in [18] present a region growing segmentation method that select incrementally pixels having similar intensity value into the same region based on this predefined criteria. In [19] authors combine Sato vesselness function and direction information into an iterative region growing method for vessel tracking. This method was extended in [20] by changing Sato filter with Frangi filter since the Sato filter is known to be more sensitive to noise. Another particular technique of non-skeleton category which have drawn a lot of attention is the Graph cuts (GC) method. The Graph cuts method was proposed as a segmentation technique that merge contextual and local image information using relation between neighboring pixels [21], the result of the graph cuts methods depends on the energy functional to minimize. In order to overcome the shrinking bias drawback of the original Graph cuts method, authors in [22] propose an energy functional that takes into consideration the probability of tabular structures using the vesselness measure, the local connectivity of vessels region and the edgeness measure.

In this work, we propose essentially to introduce the direction information in the method presented in [22] in order to guide the segmentation toward more relevant vessels. Therefore the adapted GC energy functional takes into consideration the vesselness measure, the geodesic path, an edgeness measure using the adaptive Canny detector and the direction information given by the first Hessian eigenvector. We also propose two different scale adaptations, a global one that uses the whole image to deduce the scale range and a local adaptation that divides the image into regions and computes for each region the scale limits. This local adaptation aims to reduce false positives. The validation is conducted on three datasets presenting different characteristics and the proposed method is compared with four methods from the state of the art.

The remainder of this paper is organized as follows. Section 2 provides some preliminary concepts of graph cuts method and describes the proposed method. In section 3, we present experiments and discuss the results, and section 4 concludes the paper.

2. Methods

2.1. Background

The goal is to assign to each pixel a label in a set L that can be either $\omega_1 =$ "vess" if the pixel belongs to the artery, or $\omega_2 =$ "back" if it belongs to the background. In this sec-