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A robust coronary artery identification and centerline extraction method in angiographies

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ABSTRACT

Coronary artery disease (CAD) is a leading cause of death worldwide. Although coronary CT angiography (CTA) and other new technologies emerge increasingly, conventional coronary angiography (CCA) remains as the gold standard for diagnosis of CAD, and the only way to be involved in the interventional surgery. Centerline extraction of the coronary arteries is the essential information for radiologists, and is also the foundation for a computer-aided detection (CADe) system to assist them. As the data is obtained more and more, manual extraction is impractical, a fully automatic extraction method is necessary for radiologists. However, due to the projection nature, the extraction of vessels becomes extremely difficult because of non-uniform stating caused by the contrast agent distribution and overlap of the organs. Furthermore, the shape of the blood vessels is another important information needed in clinical practice, but their identification is challenging, especially at the intersectional positions. In this paper, we propose a method to extract the blood vessel contour and identify their shapes at the intersections simultaneously. Firstly, we refine Frangi's detection result to compensate the vesselness measure, ensure connectivity and eliminate artifacts as far as possible. Secondly, we study a vessel connectedness based clustering method to identify the each blood vessel. Thirdly, in order to handle the gaps and holes in enhanced vessel image, we employ a robust method based on principle curves to extract the centerlines. Finally, We evaluate the performance of our method on 60 clinical samples in angiographies. The method performs well with respect to centerline extraction, which its average accuracy is 96.247%, sensitivity is 79.981% and specificity is 97.754%.

1. Introduction

Coronary artery disease (CAD) is one of the major cause of death worldwide in the last decade [1]. The oxygen and nutrients are required to keep the normal heart function through the coronary arteries. Currently, CAD screening is often carried out by conventional coronary angiography (CCA) and computed tomography angiography (CTA). Although CTA can provide more information on arterial calcification and vascular distortion in 3D image, it lacks of the real-time imaging and reflection ability of blood supply. Therefore, the CCA is so far the most accurate detection technology and can be provided with the most intuitive understanding of the coronary arteries. In other words, CCA is still the first screening modality on potential coronary artery disease, and it is the reference gold standard imaging technique as before. We have observed that CCA is now performed on a daily basis for complex cardiac interventions. Thus, the proposed methodology is practical in many clinical cases.

In the cardiovascular disease screening process, accurate vascular curvilinear structures tracking forms an essential and challenge step from images [2,3]. It holds great significance to describe the potential implications for the anatomy and diseases. It not only provides the coronary arteries, branches, twisted and other anatomical information, but also provides other pathological information such as calcified plaque and stenosis. And a robust coronary artery extraction algorithm is an essential part of some processing tools, because these tools are dependent on accuracy and effectiveness of it. However, it is a grand challenge due to image noise, artifacts, non-uniform staining in the CCA images, the performance

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varies easily according to the image quality. Furthermore, vascular structures also contain a variety of complex types, such as overlapping, crossing or bifurcation, especially for two-dimensional projection image. It is with great difficulty in identifying the vascular directions at overlapping or intersections. In addition, with the development of the science and technology, a large number of new imaging equipments are widespread used rapidly, manual extraction and annotation will be more time-consuming and skill-demanding. So another urgent issue to tackle is how to track the centerlines of vessels fully automatically without any user interaction.

Many studies are currently used for detection of vascular structures. The most popular method is based on Hessian matrix, which is like a filter to response the local linear features, such as the Lorenz's vesselness [4], the Sato vesselness [5] and the Frangi's vesselness [6]. However, all of these types of methods are very sensitive to the noise or artifacts. They often fail in the case of abnormal blood vessels (soft plaque, hard plaque, brackets, etc.). And the performance may not be good for a bifurcation point or a cross point, because they need to calculate the second derivative of the image.

Some other important technologies are based on machine learning to learn the filters on given image data [7–9]. In practice, the acquisition of these data is an expensive and laborious process, because a lot of training data acquisition is required in order to ensure the robustness of the algorithm and ground truth requires a lot of manpower to verify. Though machine learning can be applied to refine detection performance, learning effectiveness is limited to the classifiers in low-dimensional feature space. In the recent work, linear filters detecting curvilinear structures are determined by a dictionary learning method. The output of these filters, together with an Optimally Oriented Flux [10] and the Frangi's vesselness, are used as input for a Random Forest or a logistic regression classifiers. Graph cut (GC) technique is one of the best segmentation tools that rely on the relationship established between pixels adjacent to the model by incorporating the partial context image information [11,12]. The advantage of the solution is determined by GC and reliable energy calculated applicability. However, note that the GC's "shrink bias" problems, due to the defined energy function, and the record length is proportional to the boundary, GC will be biased in a small portion of the isotropic region [13].

In addition to the methods before mentioned, there are methods based on regional growth and active contour model [14]. The method regional growth based is the easiest way. The region is extended gradually under some criteria through the growing process of pixels. But this classical technique is suitable for the regions with high vascular contrast. If it is applied on low contrast occasions such as the pathological change, damage of blood vessels, or the presence of noise, the growing is easy to diffuse into the surrounding tissue. Active contour segmentation method can also be used in blood vessels. This energy minimization model under the guidance of the internal and external forces evolves the object boundary contour. External forces are derived from the image information, and internal forces are determined by the contour of the geometry and regularity. Active contour technology can provide a method that allows the integration of different features and models.

With regard as the centerline extraction, several approaches were dedicated to the automatic centerline extraction of the coronary tree, which were mainly based on mathematical morphology [15], model-fitting [16], medialness filter [17] and fuzzy connectedness [18]. These methods all had also some difficulties to extract the distal parts of coronary arteries or them with narrowing, calcification and motion artifacts.

The performance of centerline algorithms varies according to the detection methods or values of their parameters, therefore vessel contours cannot be sketched very precisely. Just because they are strongly dependent on the detection ability of each algorithm, error extraction may be led in. And due to the projection nature in angiography, the extraction of each vessel becomes extremely difficult because of non-uniform stating caused by the contrast agent distribution or overlap of the organ gradations. Therefore, it is essential to overcome these issues in existing algorithms and to refine the effect of vascular detection. Moreover, most existing extraction algorithms are not taking into account the shape of each vessel, particularly, at the intersections, whereas vessel shape is also an important information for the clinical diagnosis and interventions.

Overall, the vascular centerline extraction mainly consists of three steps: vessel enhancement, binary segmentation and centerline extraction. The first major contribution of our work does a post-processing of Frangi's method which was just to enhance the vessels and could not directly produce the centerline. Whereas, in order to obtain good centerlines, the intensity difference between blood vessels and artifacts should be as big as possible. Our post-processing can ensure the continuity of vessels in segmentation step via intensity compensation among neighbor pixels of Frangi's method by using Gaussian filter, therefore it can deal with trade-offs between the vessel continuity and artifacts elimination well. The second major contribution is that the same blood vessels can be clustered together via connectedness-related vascular clustering and can guarantee the accuracy and robustness in centerline extraction. Thirdly, the principal curve algorithm is employed for vascular centerline extraction which can obtain a robust result by overcoming the break-offs or gaps caused by binary segmentation. The principal curves are defined as one-dimensional curves that pass through the 'middle' of a set of p-dimensional data points, providing smooth and curvilinear summaries of p-dimensional data [19]. Fourthly, the whole framework is an innovation for the vascular centerline extraction. The flowchart of our proposed method is shown in Fig. 1. Experiments using real clinical images demonstrate a numerical and visual superiority of the proposed algorithm.

The remaining part of the paper is organized as follows: Section 2 describes a method for extracting the centerline and the depth reasoning algorithm based on directional connectedness clustering. Experimental results and discussion expressed in Section 3. Then, Section 4 is the conclusion and future outlook.

2. Methods

2.1. Vessel detection (refined Frangi's vesselness filter)

The curvilinear structure detection is a necessary step in vessels tracking. The strength and direction of blood vessels can be prone to be characterized by the eigenvalues and eigenvectors of Hessian matrix, because it is a square matrix of second-order partial derivatives of a image function. We employ a widely used vessel detection method as preprocessing step based on vesselness measures, which was proposed by Frangi et al. [6]. This method can get the direction of the tubular structure and to calculate the probability of the local blood vessels. And it can take a full consideration to all the eigenvalues and the blood vessels can be interpreted to the intuitive geometric features. That is therefore a way to find a coarse tubular geometry in the vascular detection. Given an image $f(x, y)$:

$$H = \begin{bmatrix} f_{xx} & f_{xy} \\ f_{yx} & f_{yy} \end{bmatrix}, \tag{1}$$

$$f_{xx} = \frac{\partial^2 f}{\partial x^2}, \quad f_{yy} = \frac{\partial^2 f}{\partial y^2}, \quad f_{xy} = \frac{\partial^2 f}{\partial xy}, \tag{2}$$

$$\lambda_1 = K - \sqrt{K^2 - Q^2}, \quad \lambda_2 = K + \sqrt{K^2 - Q^2}, \tag{3}$$

where $K = (f_{xx} + f_{yy})/2$ and $Q = \sqrt{f_{xx} f_{yy} - f_{xy} f_{yx}}$.