CORONARY ARTERY TREE SEGMENTATION USING MULTI-CLASS GRAPH CUTS AND MATHEMATICAL MORPHOLOGY

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ABSTRACT

Accurate coronary artery tree segmentation in Computed Tomography Angiography is of great significance for clinical practice. In this paper, a framework dedicated to coronary tree segmentation was proposed. Based on multi-class Graph Cuts classification, the prior knowledge of intensity distribution is incorporated. Then, a novel mathematical morphology method adapted from hit-or-miss transform was presented to robustly detect the vascular structures. Quantitative and qualitative tests were performed on 15 cases gathered from 5 patients. The experimental results showed that our method can segment coronary artery tree effectively.

Index Terms**—** Coronary Artery Tree, Segmentation, Graph Cuts, Mathematical Morphology

1. INTRODUCTION

Cardiovascular diseases (CADs) remains to be the leading cause of death worldwide [1], therefor, quantitative description of coronary artery tree is in crucial need for diagnosis and treatment of CADs and relevant diseases. Due to the heterogeneity of the size and intensity of coronary arteries and the interference of surrounding cardiac structures, especially considering structures with similar HU values in CT Angiograph (CTA), accurate and complete coronary artery tree segmentation appears to be a very challenging problem. In addition, manually delineated segmentation for volumetric data is still an extremely laborious and indeterminate task, so the size of labeled dataset with very high labeling quality and representativeness is quite limited. In addition, due to the growing need for analyzing multi-phase 3D motion of heart and coronary artery, new segmentation schemes with much lower time consumption and minimal user interactions are in demand.

In recent years, numerous methods for 3D vessel segmentation and centerline extraction have been presented. Early reviews can be found in [2] and a recent one is given in [3]. Among existing methods, vascular structure enhancement techniques such as Hessian based methods [4] and Flux based methods [5] are particularly popular. However, the high proportion of false positive (FP) response of non-vessel structure has not been effectively addressed for those methods. Recent works [6] presented multiple hypothesis approach to improve the robustness by combining multiple segmentation techniques to form a hybrid method. A supervised learning-based framework was proposed in [8] for coronary artery tree segmentation which was trained and validated with only 6 datasets.

Low-level image processing operators such as erosions and dilations are commonly used in medical image analysis for post processing of binary images. However, their strength has not been effectively exploited. In particular, binary mathematical morphology has not yet been considered for vascular structure segmentation to our knowledge. A novel region-grow method based on grey-level mathematical morphology techniques has been consider for coronary segmentation in [7], while suffers from the drawbacks of region-growing based schemes.

In this paper, instead of focusing only on the frequently explored main coronary vessels, our method aims to segment the whole coronary tree branches that can be visually identified. The rest of the paper is organized as follows: 1) The motivation for multi-class labeling in our method is explained. 2) A multi-class Graph cuts labeling scheme was introduced. 3) A novel 2-stage binary mathematical morphology method was presented for detection vessel structure on our labeled image. 4) Quantitative and qualitative test was performed on datasets gathered from 5 patients.

2. METHOD

For the whole coronary artery tree, the intensity of vessels regions showed a large range of variation. However, the histogram of HU values for the whole cardiac region is observed to have a specific profile (Fig. 1). Based on this knowledge, our method is designed to separate the cardiac region into distinctive categories: background, cardiac

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region with lower HU values and carotid artery region with higher intensity and labeled as $c \in \{B, L, H\}$.

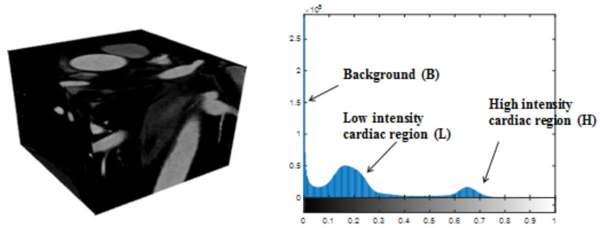

Fig.1 3D CTA Cardiac region volume and its HU histogram

Due to the recognizable intensity difference between the vessel pixels and their adjacent non-vessel pixels, vascular structures is appeared to be the holes in 3D binary images. Our 2-stage morphological operation is designed to detect the vascular structure in cardiac region. Moreover, coronary arteries tree can be selected with single seed point

2.1 Multi-class graph cuts

Graph cuts method considers image segmentation as pixel-labeling problem. Object of interest and the background are mapped into certain labels by minimizing specific energy function. In particular, graph-based approaches have proved its efficiency for various issue and organ segmentation tasks [8]. In this work, we use it for producing labeled masks of mentioned subregions. Suppose the pixels and their neighbors in our volumetric data are represented as a directed graph $G=(\nu, \varepsilon)$. The standard form of energy function [9] is written as

$$E(x) = \sum_{p \in \nu} \theta_p(x_p) + \sum_{(p,q) \in \varepsilon} \theta_{p,q}(x_p, x_q). \tag{1}$$

The data term (first term) of the energy function normally adopts intensity model of the object, a simple two-class intensity model was used in [10] for the energy function of their graph cuts-based vessel segmentation method. In this paper, we used a three-class labeling scheme for coronary artery tree segmentation, where the cardiac region was labeled as In view of the pattern illustrated in the HU histogram of cardiac region, we simply extend the typically used 2-class data term to

$$\theta_p(x_p) = \sum_{p \in \nu} 1 \cdot (x_p = c) \cdot (I_p - \mu_c)^2, \tag{2}$$

where the $1 \cdot ()$ operator returns 1 when the condition is satisfied. The Quadratic Pseudo Boolean Optimization (QPBO) method [9] was employed to find the minimum cut of the graph.

As a result, cardiac region is divided into three subregions combined with anatomical context. During the labeling process, we assume it is impossible for any vessel pixels to be classified as pure black background. And any pixels of black background region will not be labeled as high intensity objects.

2.2 Mathematical Morphology

Hit-or-miss transform (HMT) is a classic morphological operation that detects specific patterns in binary image, which is derived from erosion operation and used to locate specific objects [11]. The hit-or-miss transform of a given binary image A is defined as:

$$A \odot B = (A \ominus C) \cap (A^c \ominus D), \tag{3}$$

where $B=(C, D)$ and the two structuring element C and D need to satisfy the condition $C \cap D = \varnothing$. A^c is the set complement of A. HMT can be adapted for addressing complex tasks. In this paper, we proposed a novel two-step morphological method based on HMT and vessel enhancement filter with obtained labeled image.

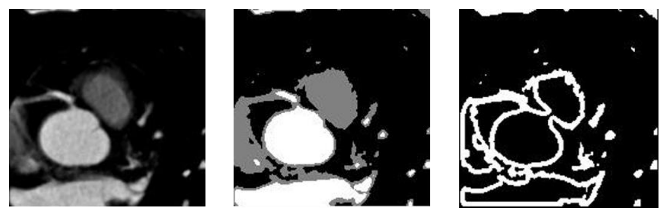

Fig. 2 Left to right: original image, labeling result by multi-class Graph Cuts and the result of first morphological operation.

The First step operation aims to detect the elongated holes in binary image, and it is defined as

$$M = \tilde{B} \cap \overline{((\tilde{L} \cap L \ominus C) \cup (\tilde{H} \cap H \ominus D))}. \tag{4}$$

The structuring element D was set to $\varnothing$ and C is set to a sphere binary mask. This HTM adapted operation was implemented on L and H respectively and combined afterwards. We used the background mask to emphasis the existence of zero valued background.

As showed in Fig 2. , plenty of non-vessel edges are detected as well. We introduced the vesselness vascular structure filter propose in [4] for further removing the falsely detect pixels. We intended to remove the false edges in high intensity region by keeping the mask obtained from a high threshold of vesselness and removing the dilated H mask. For false edges in the low intensity region, a low threshold of vesselness was used. The second operation is organized as:

$$X = M \cap V_1 \cap \overline{(M \cap H \oplus D) \cup V_2} \tag{5}$$

where V_1 and V_2 are binary vesselness processed masks with a higher and a lower threshold. The final segmentation result is showed in Fig. 3 with our 2-stage morphological operation.

Fig. 3 Left to right: dilated mask of high intensity region and the result of second morphological operation.

3 EXPERIMENT

Our 20 CTA scans for training (5) and validation (15) are gathered form 5 patients, and each consist of 4 data frames randomly selected from a 21-phases CTA series. The voxel size of our dataset is $(0.7411 \pm 0.0454) \times (0.7411 \pm 0.0454) \times 0.5mm^3$. And each of them was resampled to ensure the data to have equalized axial resolution. One fixed region of interest (ROI) was used for the entire experiment. With the supervision of an expert, two people denoted the ground truth masks with an interactive image segmentation tool. Any pixels can be recognized to belong a coronary artery branches were marked. The masks then are skeletonized to vessel centerlines using Matlab built-in function describe in [13] for evaluating proposed method. The evaluation is based on the manually delineated mask and corresponding centerlines.

The two thresholds for the data term of the energy function was fixed as μ_L=0.2 and μ_H=0.75 based on our observation to the histogram of cardiac regions of various - patients. No interactions were needed in our labeling process, the correspondence of subregions was identified with their mean the fixed thresholds.

The size of volume for Graph cut computation was set to $165 \times 165 \times 170$. The size of the erosion operators in our binary morphological method is estimated to be the largest vessel radius of coronary arteries as $R_{\max} = 4$. The vesselness thresholds are set to be 0.3 and 0.15 respectively for V_1 and V_2.

For the evaluation of the accuracy of extracted centerlines, we firstly removed the small connected region from resulting masks. In order to focus on the coronary artery rather than other vascular structures, we put two seeds points respectively to select connected regions of the left and right coronary arteries in the region of interest. An overlap measure and average distance were computed. Proposed method describes the centerlines in binary masks. The correspondence between our results and reference standard is not easily built with much interaction, we competed the Sensitivity coefficient as

$$OV = \frac{TP}{TP + FP}, \tag{6}$$

while assuming $TP = TN$ compared to DSC coefficient. The average distance between the reference standard and our results is calculated as

$$d(l_1, l_2) = \frac{1}{N} \sum_{j=1}^{N} d(l_2(i), l_1). \tag{7}$$

Table 1 Overlap measure and average distance compared to manually delineated ground truth

	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5	Average
Overlap	89.4%	60.6%	54.4%	63.1%	48.5%	63.2%
Average Distance /pixel	0.65	0.99	1.01	1.07	0.98	0.94

Distance measure was computed only when a centerline segment was within the range of ground truth mask. Table 1. summarizes the quantitative results for the 15 cases. Qualitative results are given in Fig 4. The radius of coronary was set to a fix value for visualization. The vascular structures that can be visually identified were well detected by our method.

For our dataset gathered from 5 patients, our methods obtained the mean overlap result of 63.2% and a mean distance of 0.94 times of pixel size which is under the resolution of the single voxel. Compared to the morphological method described in [11], our method examined the segmentation results with standard evaluation method and expends that scheme to not just the local information of HU values of coronary arteries. As showed the qualitative results in Fig 4. Our method extracted the most of the branches of coronary arteries in cardiac region that is recognizable.

4. CONCLUSION

In this paper, we propose a dedicated framework for coronary tree segmentation. The prior knowledge of intensity distribution for CTA image is incorporated based on multi-class Graph Cuts labeling. Then, a novel mathematical morphology method adapted from hit-or-miss transform was presented to robustly detect the vascular structures. As a result, the centerlines of coronary artery tree were extracted after a skeletonization procedure. Quantitative and qualitative experiment on 15 cases gathered from randomly selected phases in a cardiac cycle. Promising segmentation results are achieved compared to manually denoted ground truth. Future work will address the segmentation for a volume series gathered from a single patient. And we will also work on building patient-specific coronary artery tree model for clinical practice further.

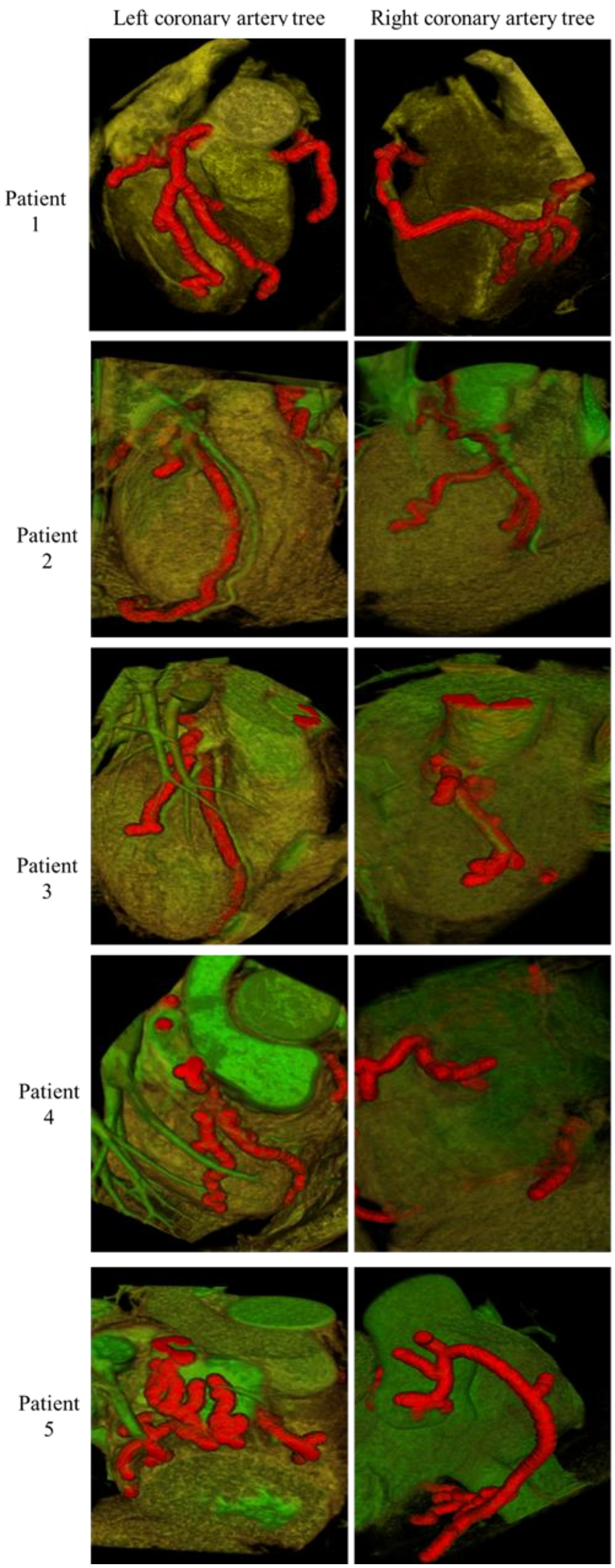

Fig. 4 **S**egmentation results of Left coronary artery tree and right coronary artery tree highlighted in red.

5. ACKNOWLEDGEMENT

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