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# Graph cut based automatic aorta segmentation with an adaptive smoothness constraint in 3D abdominal CT images

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ABSTRACT

Aorta segmentation is clinically important as it is a necessary step towards accurate assessments of some aorta disease. In the paper, we present a graph cut based method for automated aorta segmentation. In our method, a discriminative integrated feature (DIF) and a novel adaptive smoothness constraint are designed. DIF consists of low level features and other discriminative features including eigenvalues of Hessian and local self-similarity descriptor. DIF and random forests (RFs) are used to generate the probability maps. The probability maps containing learning information from RFs are more accurate than traditional probability maps generated based on intensities directly. The negative logarithm of the probability maps serves as the penalty term in a cost function. Additionally, a novel adaptive smoothness constraint is imposed to ensure a smooth solution. The adaptive smoothness term is constructed by DIFs and data-driven weights. Two kinds of data-driven weights are developed based on the idea that the discontinuity of two neighboring voxels with different labels should be distinct with two neighboring voxels with the same label. The final segmentation is obtained by optimizing the cost function using graph cuts. We evaluate the proposed method through challenging task of abdominal aorta segmentation in 3D CT images. With average dice metric (DM) $>$ 0.9690 on the test set, our experimental results demonstrate that our method achieves higher aorta segmentation accuracy than existing methods.



## 1. Introduction

Aorta disease is one of the primary factors that threaten people's health [1,2]. The aorta segmentation is of much importance for the diagnosis of aorta disease. For example, abdominal aorta segmentation is a necessary step towards accurate assessments of abdominal aortic aneurysms. Accurate aorta volume in conjunction with other parameters contributes to predicting the pathological stage. And information on the shape, size of the aorta is essential for the design of treatment planning. Conventional image segmentation methods such as watershed, region growing and intensity thresholding method perform poorly in aorta segmentation since they all cannot deal with large variations very well [3,4]. In light of this, many kinds of advanced methods have been proposed in the recent literature for aorta segmentation [1,5–15]. The existing aorta segmentation methods can be classified into three categories, i.e., the methods based on standard techniques, the embedding shape priors methods and other graph cut based methods.

The methods based on standard techniques mainly include the methods of multi-atlas, active and statistical shape models. Isgum et al. [5] proposed a method based on multi-atlas to segment aorta in CT images. It required registration and fusion to determine the aorta region. It was time consuming and space consuming.

The embedding shape priors methods which use shape priors to restrict the final segmentation to some pre-defined shapes are conceivable [12,15]. But some constraints of these methods are high-order functionals which lead to difficult optimization problems. The embedding shape priors methods can mainly be divided into two categories. The first is to add shape priors to level set methods [15]. Level set methods with shape priors are able to obtain impressive results, but they are slow and often lead to complex optimization problems which are hard solved by standard powerful optimizers such as convex-relaxation techniques. The second is to add shape priors to graph cut methods [12]. In traditional graph

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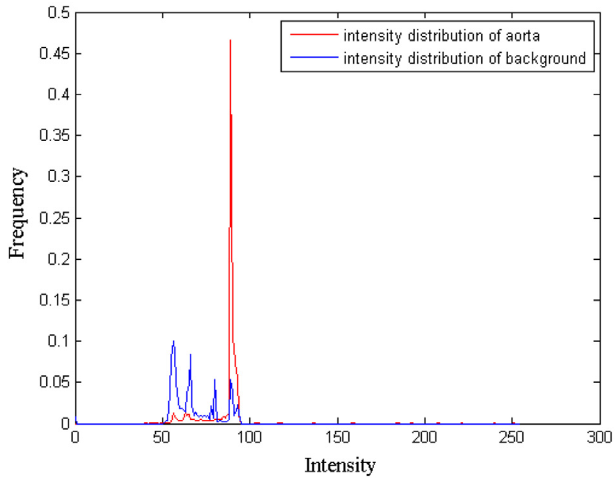


**Fig. 1.** Intensity distribution of voxels in aorta region and background region within COI. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

cut method [16], a penalty term is used to compute the cost for assigning a pixel to 'object' and 'background' and a smoothness term serves to ensure the smoothness in the boundary. Graph cut methods with shape priors are inclined to achieve global minima and are faster than level sets [17]. However, just like most level set methods, these methods are either restrictive on a specific object class shape or a generic shape prior. A specific object class shape prior often leads to underfitting while a generic shape prior often over estimates the aortic wall. Ayed *et al.* [12] proposed a method based on a generic shape prior which was a high-order fractional term for segmenting the aorta. The high-order fractional term leaded to a hard optimization problem and sometimes over estimated the aortic wall.

Other graph cut based methods did not use shape priors but other priors. Duquette et al. [11] proposed a semi-automatic method which was based on graph cut theory and needed little human intervention. Unfortunately, the semi-automatic method was not convenient.

Almost all these existing methods used the intensity directly and few used low level features, which caused they sometimes performed poorly. Moreover, most of these methods were time consuming or space consuming. These necessitate the design of robust and convenient aorta segmentation algorithms. Aorta segmentation is a challenging task in many aspects. There are two most glaring challenges. The first one is intensity similarity between some voxels within aorta region and surrounding tissues region. To further illustrate this point, we calculated the intensity distribution of aorta region and background region within the cuboid of interest (COI) after the intensities were normalized to 0–255. As can be seen from Fig. 1, the red curve and the blue curve represent the intensity distribution of the aorta and the background, respectively. We can see the overlap is obvious since the area of the overlap is not small. Besides, we use some images to demonstrate this challenge. As is shown in Fig. 2, some adjacent tissues have the similar voxel intensity to the aorta. The second challenge is lack of clear boundary for the aorta region due to the similar intensity of voxels near the boundary, which is shown in Fig. 3 where the red region represents the aorta. We can see untrained eyes can hardly recognize the accurate boundary of the aorta.

In this paper, we propose a graph cut based method for automatic aorta segmentation with a novel smoothness term. In our method, we design a discriminative feature to solve the intensity similarity problem and develop an adaptive smoothness term to ensure a smooth boundary.

Discriminative features in image segmentation are necessary for many applications, in particular when the target has similar intensities with background [18–20]. Therefore, we design a discriminative integrated feature (DIF) for aorta segmentation constituted of low level features, context feature, eigenvalues of Hessian and local self-similarity (LSS) descriptor [21]. The proposed DIF captures comprehensive information containing local shape, contextual information and internal geometric layouts. The low level features presented by intensity, texture and curvature exploit visual cues and local shape. But low level features are not enough to obtain fine segmentation in that they are similar between the aorta and the surrounding tissues as to many images obtained from some subjects. Therefore, contextual information is considered. Additionally, we introduce eigenvalues of Hessian and LSS descriptors to the task of aorta segmentation. The eigenvalues of Hessian are used to examine the probability that a vessel is present locally [22–24] while the LSS descriptor captures internal geometric layouts of self-similarities within local regions [21]. So the proposed feature takes into account both the intensity similarity and the shape priors. DIFs are used to generate probability maps containing learning information from random forests (RFs). The probability maps contribute to formulating the penalty term in a Markov random field cost function.

The lack of clear boundary for aorta region is caused by the similar intensity of voxels near the boundary. In traditional graph cut method [16], the differences of intensities are used as the smoothness term directly, it cannot perform well in aorta segmentation because the intensities of voxels near the boundary between the aorta and background are similar. Therefore, we develop a novel adaptive smoothness term to address this issue.

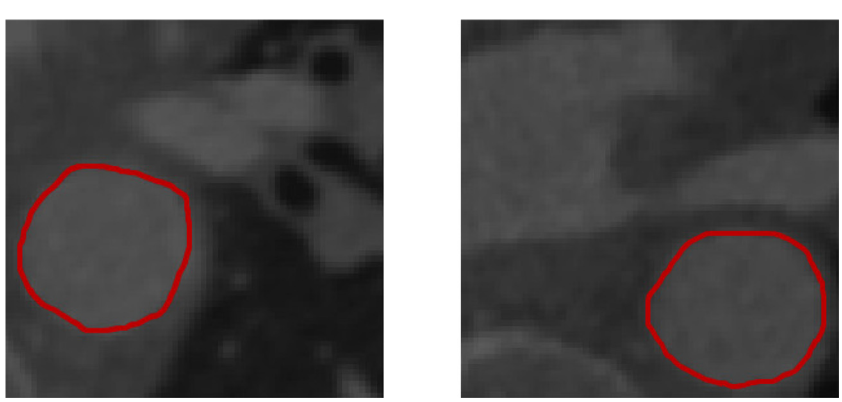

**Fig. 2.** Two axial slices with the red lines corresponding to the ground truth. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)