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Automatic Segmentation of the Aorta in Cardiac Medical Images

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ABSTRACT

Automatic aorta segmentation from three dimensional image data is very important for treatment planning and diagnosis of cardiovascular diseases, which are the leading cause of death in the developed countries. A number of techniques are available but most of them need user interaction and require very high contrast of input images that increase the patient exposure time inside the machine. In this paper, we have proposed a novel segmentation pipeline that can automatically segment the aorta from low contrast three-dimensional data. Input images are pre-processed using gradient and sigmoid techniques in order to identify real edges and increase contrast of the image. Hough transform is used for automatic detection of circular shape of aorta that is followed by a three dimensional connected threshold algorithm to delineate the aorta from other objects. The results show that our technique can automatically segment the aorta faster than existing techniques. The algorithm uses low contrast image data, requires no user interaction and no parameters tuning. The proposed technique, with minor modifications, can also be used for semi-automatic segmentation of other organs in the human body.

1. Introduction

Computer-aided diagnosis using medical image segmentation is a very important field that helps doctors and clinicians in the detection of abnormalities, treatment planning and analysis [1]. The aorta is the largest artery in the human body that supply oxygenated blood to all parts of the body. Segmented aorta can be used in medical diagnosis, treatment planning and analysis of cardiovascular diseases (CVD) which are the leading cause of death in the developed countries [2, 3]. Automatic segmentation of the aorta from low contrast three dimensional (3D) Magnetic Resonance (MR) and Computed Tomography (CT) images is a very challenging problem in health care industry and has been studied extensively in the last few decades.

There are various factors such as anatomy variation, homogeneity, disease type, non-uniform object texture, noise, quality, input nature, low contrast and special characteristics of image continuity that make the segmentation process very challenging. In order to overcome the above challenges, various pre and post processing techniques can be used. For segmentation of homogeneous regions, the challenge is to identify the real boundaries of organs. Common segmentation techniques can segment objects from high contrast images but fail to segment images of low contrast having no significant variation in intensity values surrounding the region of interest. A few algorithms are available that can segment the aorta from low contrast input images but take very long time to produce the required output [4-10]. There are a variety of approaches for segmentation of medical images ranging from simple one such as thresholding, to more elaborate techniques including pattern recognition, template matching, artificial intelligence, neural networks and tracking based approaches [11-13]. Region growing is a pattern recognition approach that starts segmentation from a seed point and incrementally recruits pixels to a region based on a predefined criteria [12]. It is a simple and robust method of segmentation that is rapid and free of tuning parameters. Due to the user control during seed selection and easy implementation makes it a better choice for separating an object of interest.

The limitation of region growing technique is that it often requires user interaction in the form of seed points. Users have to provide initial start points from which the algorithm starts segmentation of the desired object. Similarly, over segmentation of image may occur due to variation in image intensity, overlapping regions and noise present in the image. However, to overcome these limitations, pre and post processing techniques can be applied on the image to make the segmentation automatic and control the region growing process. In modern technology that produces hundreds of slices per minute, manual segmentation is impossible and hence requires fast and robust segmentation with minimal user interaction.

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In this paper we have first reviewed the existing automatic segmentation techniques and then proposed a segmentation pipeline for fully automatic aorta segmentation. We have compared the performance of the existing segmentation techniques for aorta segmentation with the proposed algorithm based on afew criterion functions such as input image type, dimension, result type, and computation time.

2. Literature Review

Existing algorithms for segmentation of the aorta can be classified into semi-automatic or automatic techniques. In semi-automatic segmentation, users have to provide input parameters to segment the desired objects [14]. Moreover, semi-automatic segmentation is very time consuming and requires experts for segmentation.

Automatic segmentation detects, automatically, the region of interest (ROI) and performs segmentation without any user interaction. With this approach, large number of cases can be handled with the same accuracy and the output is not affected as a result of fatigue, data overload or missing manual steps. Similarly, automatic segmentation is not affected by the brightness and contrast of the display screens.

Aorta segmentation from low contrast MR and CT images is a very challenging problem. Most of the algorithms available for aorta segmentation are semi-automatic which require manual initialization and parameter tuning [15-31]. A vessel segmentation algorithm presented by Wink [26] starts an iterative tracking process for vessels extraction. For high contrast images the algorithm performance is good but fails to mark boundaries for low contrast images. Katz [27] presented a neural network based algorithm for aorta detection. Zhao [28] presented an automatic algorithm by combining level sets and optimal surface technique for segmentation of the aorta in four-dimensional (4D) cardiovascularMR image data. A 3-D cylindrical parametric intensity model was developed by Worz and Rohr [29] that needs user interaction for initialization. Verdon [30] proposed a generalized cylinder-based vessel extraction and border estimation model to extract vessels from 3D image data.

In medical imaging literature, only a few algorithms can segment the aorta from 3D medical images automatically. Pohle [4] has proposed an adaptive region growing algorithm for fully automatic medical image segmentation that learns its homogeneity criteria automatically from the characteristics of the ROI. The algorithm can segment 3D CT and MR image data and it can be used for semi-automatic as well as fully automatic segmentation. However, overlapping regions of the image may affect the segmentation results and the algorithm is sensitive to noise. An automatic aorta tracking algorithm from MR data is presented by Rueckert [5] that uses Markov random field framework to automatically segment the ascending and descending aortas from MR images, without any user interaction. The limitation of the algorithm is that, it is for two-dimensional (2D) image data and cannot handle the curved aortic arc elegantly. Moreover, the segmentation is based on estimation and is sensitive to noise. Kovacs [6] has proposed a model-based segmentation in which a centreline is generated using Hough Transform (HT) method [32] and then an initial rough deformable model is generated using the aorta centreline and diameter. The algorithm can automatically segment 3D image data but it takes an average of six minutes for segmentation, and hence is very time consuming.

A part-based approach that segments the aorta from 3D C-Arm CT images using Marginal Space Learning (MSL) technique is proposed by Zheng [7]. Despite remarkable robustness, this work is not considering the upper carotid arteries. Moreover, if no aortic root is detected in the image, the input volume is rejected and the algorithm requires very high contrast input images for segmentation. A 3D level set approach for segmentation of the aorta in low contrast chest CT images was developed by Kurugol [8]. Hough Transform is used to automatically detect aorta in the image and a tubular aortic surface is reconstructed from the centreline and radius functions. The algorithm is very affective for segmentation of the aorta and can segment low contrast images. However, a large number of parameters in level set approach and transformations increase the segmentation time of the algorithm.

An automatic segmentation approach is suggested by Flehmann [9] that combines Fast Marching (FM) [33] and HT methods for fully automatic aorta segmentation. The algorithm performs segmentation in a slice-wise manner that starts from the middle slice of the stack of image data and search in 10 % of the neighbouring slices for three circles. It finds an initial start point by searching circles with strongest Hough peaks in the gradient magnitude filtered image slices. The algorithm takes an average of 22 seconds to segment complete aorta from a 3D image. An automatic approach for segmentation of the thoracic aorta from low contrast CT images is proposed by Kurkure [10]. The algorithm can segment low contrast images but takes a long time for segmentation due to the Hough Transform applied to obtain a series of optimal best fit circles for the detection of different parts of the aorta. Large number of transformations increases computation time.

Following are the common problems with existing approaches due to which clinicians still use manual segmentation instead of available automatic and semi-automatic segmentation techniques.

- Most of the segmentation algorithms require very high contrast of input images that increase patient exposure time inside the machine.
- Many of these algorithms segment just a well-defined part of the aorta and cannot handle variation of anatomy. There exist variations in the anatomical structure of the aorta among different individuals that may be due to age, height, weight, disease or other natural factors. This variation of anatomy makes the process of segmentation challenging and a single algorithm with same criteria may not work to segment the complete aorta. Most of the algorithms use the circular shape of the aorta that helps in the detection process but fail to segment when the aorta is not circular. These algorithms segment the ascending or descending aorta and cannot segment the complete organ.
- Some of the techniques are estimation based that require parameters tuning and are not reliable to be used in practical applications.
- Some of these algorithms use large number of transformation and pre processing that increase computation time of segmentation.

In this paper, we have proposed a novel segmentation pipeline that overcomes some of the challenges faced in automatic segmentation of the aorta from 3D images. The proposed segmentation technique can automatically segment complete aorta (ascending aorta, descending aorta, aortic arc, aortic root and carotid arteries) from low contrast 3D images, faster than the existing algorithms.

3. Proposed Segmentation Pipeline

There are three main steps in the proposed segmentation pipeline. In the first step the low contrast 3D input image is pre-processed using gradient and sigmoid image processing techniques. Gradient image filter [34] is used to identify the real boundaries of the object from a homogeneous region. Sigmoid filter [34] is applied on the gradient image to increase contrast by mapping a new intensity range of values to the objects and separate the homogeneous regions. The second step is the automatic detection of the aorta from other objects. Circular Hough transform [32] is used to detect the circular shape of the aorta and to calculate the seed point for segmentation algorithm. In the third step, a 3D connected threshold filter [34] is used that starts segmentation from the seed point and delineate the aorta from the rest of the objects. Fig. 1 shows the various steps in the proposed pipeline.

For segmentation we have used the Insight Segmentation and Registration toolkit (ITK) [34], which is an open source and cross platform software system for performing multidimensional data segmentation and registration. The details of these steps are given in the following section.

3.1 Input Image

The input to the algorithm is a volume image that consists of a large number of 2D images. Each 2D image is called a slice as shown in Fig. 2. High resolution images provide more information and play a very important role in making correct diagnosis. However, high resolution images require more acquisition time and increase patient time inside the machine. The goal of the proposed algorithm is to perform segmentation on low resolution images and assign a new range of intensity values by applying contrast enhancement techniques in order to reduce acquisition as well as patient time inside the machine.

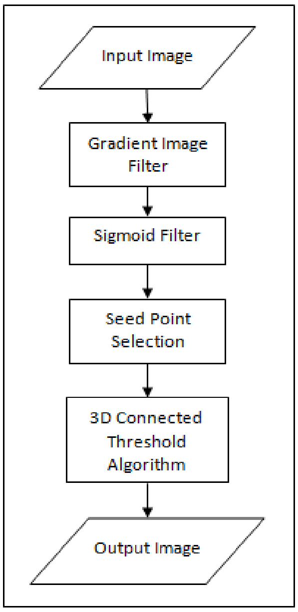

Fig.1: Proposed pipeline for the aorta segmentation in low contrast cardiac medical images

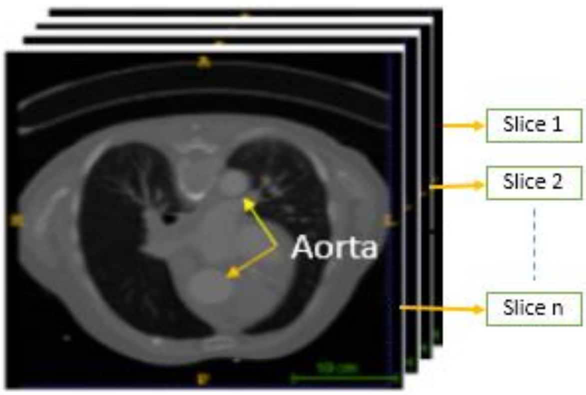

Fig. 2: Input MRI volume image that consists of a large number of 2D images

3.2 Pre-Processing

Pre-processing on the low contrast images is performed in such a way that it separates the objects connected to the aorta and increases contrast by assigning a new range of values to the pixels. For this purpose, sigmoid image filter is applied on the image after gradient magnitude image filter. Details of this method are given as under.

3.2.1 Gradient magnitude function

Gradient magnitude image filter [34] helps in the determination of objects contours and separates homogeneous regions (Fig. 3 (a)). The function takes a value of sigma that is provided according to the homogeneity of the input.

3.2.2 Sigmoid function

After real edges and contours detection, sigmoid image filter [34] is applied on the image to transform intensity values. Sigmoid image filter maps a specific range of intensity values to a new range of values by making a very smooth and continuous transition in the borders of the range. Sigmoid image filter uses S shaped function called logistic function. Using gradient and sigmoid image filters we can get high contrast images of the original homogeneous images (Fig. 3 (b)).

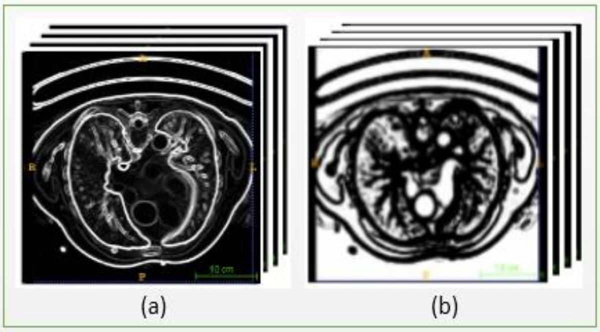

Fig. 3: Pre-processing of the input image: (a) Gradient magnitude image filter that helps in the determination of objects contours and separation of homogeneous regions (b) Sigmoid image filter that transforms intensity values and enhances the contrast of the image

3.3 The Aorta detection

The proposed algorithm automatically identifies the aorta from other objects without user interaction and parameter tuning. There are various other objects in the input image and the segmentation algorithm requires the seed point of the object to be segmented. The circular shape of the aorta on image slices helps its automatic detection from other objects. Hough Transform filter is used to automatically search one circle with strongest Hough peak as shown in Fig. 4. A range of values of radii are provided for detection of circular aorta. The algorithm finds the image middle slice, on which two circles represent aorta. One circle is of ascending aorta and the other is descending aorta with different radii. The proposed algorithm requires one circle for the detection of the aorta. If the algorithm fails to detect first one, then the second circular shape is detected that is also aorta. The centre of the circle is calculated and is provided as a seed point to the segmentation algorithm.

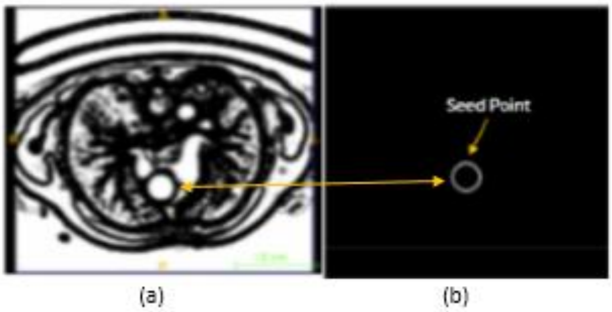

Fig. 4: Seed Point Detection: Automatic detection of the circle using Hough Transform that acts as a start point for segmentation algorithm

3.4 Segmentation

Connected Threshold algorithm [34] is used for faster segmentation of the aorta. The algorithm starts from the seed point and grows the region in x, y and z directions until object connectivity is found. The algorithm stops segmentation when the aorta is separated from the image. To remove aortic valves and other undesired regions from the aorta, first erosion operator is applied on the image and when the aorta is separated then the same amount of dilation is applied to add the pixels removed during the process of erosion. The use of connected threshold algorithm makes the segmentation of the aorta very fast as compared to other segmentation techniques. Fig. 5, the circular objects represent the two parts of the aorta on one slice.

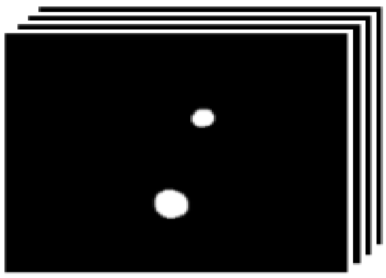

Fig. 5: Aorta Segmentation: The two circles represent the two parts of the aorta on one slice of 3D image that are separated from the image using connected threshold algorithm

4. Experiments and Results

We have tested our algorithm on 27 sets of real MR images with slices ranging from 30 to 300. The images of each set have different resolution, contrast and number of slices. The experimental result of one MR image is shown in Fig. 6. The size of the original low contrast input image is $256 \times 256 \times 34$ with voxel size as $0.70 \times 0.70 \times 5$ mm^3. We have compared the accuracy of the segmented result by comparing it with the manually segmented aorta as shown in Fig. 7. Accuracy of a segmentation algorithm is usually evaluated by comparing the result with manual segmentation due to unavailability of gold standard. We have qualitatively evaluated the accuracy of the proposed method by comparing it with manually segmented results and have calculated the difference (Fig 7). Based on the difference of segmentation results, variability of manual segmentation, unavailability of original source data and lack of gold standard, quantitative comparison is not reliable.

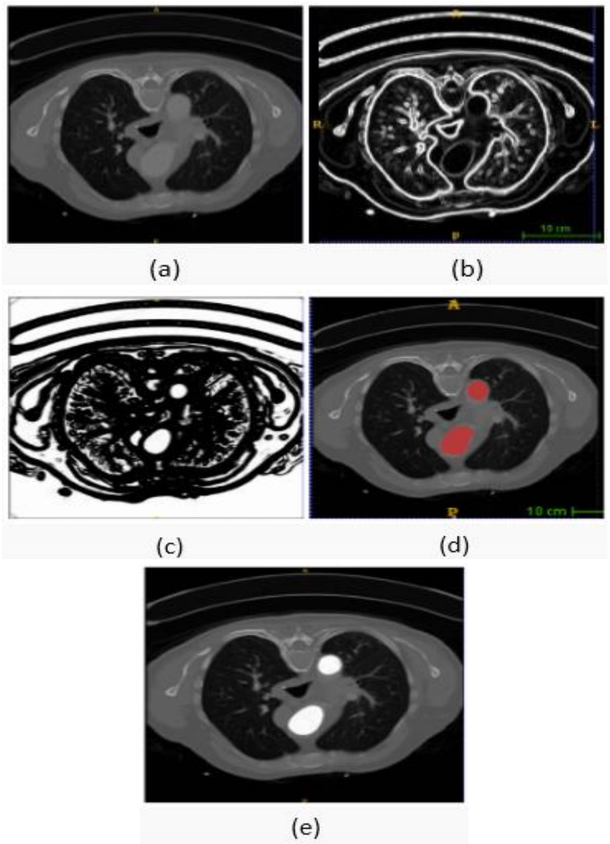

Fig. 6: Segmentation of the Aorta: (a) Original image dimension is 256 X 256 on XY plane and the number of slices is 34. (b) Gradient image (c) Sigmoid image (d) Manual segmentation of the aorta using ITK-SNAP (e) Automatic segmentation of the aorta using the proposed technique

Table 1 shows the comparison of the proposed technique with the existing automatic aorta segmentation algorithms. Algorithms are classified on the basis of resolution information of the image and effect of anatomy variation. Some of the existing algorithms are much faster [5, 7] but there are some problems with these algorithms. The algorithm proposed by Rueckert et al. [5] takes 3 seconds for segmentation but is for 2D segmentation and requires high resolution images. Similarly, the technique proposed by Zheng [7] takes 1.4 seconds for segmentation but is based on estimation, requires high resolution images and cannot segment carotid arteries. The proposed algorithm takes six seconds for segmentation of the complete aorta from low contrast images.

Table 1: Comparison of the automatic segmentation algorithms for segmentation of the aorta from cardiac images

Segmentation Algorithms	Year	Input Type	Dimen-sion	Image Contrast	Time (Sec-onds)
Rueckert et al. [5]	1997	MRI	2D	High	3
Pohle et al. [4]	2001	CT/ MRI	3D	High	16
Kovacs [6]	2006	CTA	3D	Low	360
Zheng et al. [7]	2010	C-arm CT	3D	High	1.4
Flehmann et al. [9]	2011	MRI	3D	Low	22
Proposed Algorithm	2016	CT/ MRI	3D	Low	6

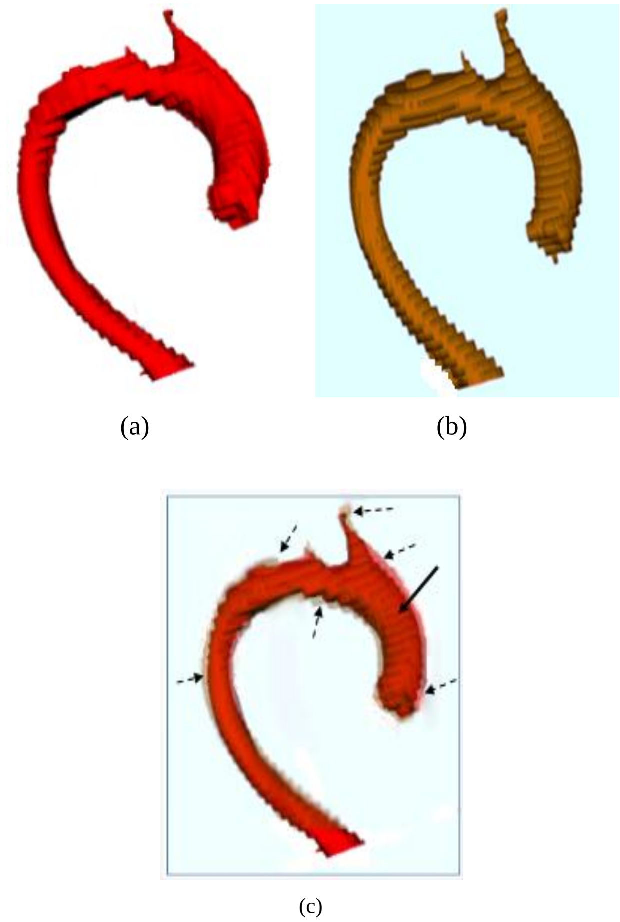

Fig. 7: Visualization of the segmented aorta: (a) Manually segmented aorta using ITK-SNAP (b) Automatic segmentation of the aorta using the proposed approach (c) Transparent image of the aorta where dotted arrows represent the manually segmented aorta while the solid arrow represents the automatic result.

5. Conclusion

The proposed segmentation algorithm is able to segment the aorta from low contrast 3D image without user interaction. We have implemented the proposed technique on cardiac MR/CT image data and compared its performance with existing automatic techniques available for aorta segmentation. In a real application environment users can interact directly with application for increasing accuracy and segmentation of a desirable object. The advantage of the algorithm is that it not only works for fully automatic segmentation of the aorta but can also be used as a semi-automatic segmentation of other objects in the image.

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