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Aorta Segmentation and Blood Flow Obtained from Phased Contrast MRI Based on an Active Contours Approach.

S. Rosas-González[1], E. R. Arce-Santana[1], A. R. Mejia-Rodríguez[1], G. Rizzo.[2]
[1] Facultad de Ciencias, UASLP, San Luis Potosí, México.
[2]Institute of Molecular Bioimaging and Physiology (IBFM)-CNR, Milan, Italy.

Abstract— **In this paper, a segmentation method based on an active contours algorithm capable to detect not well-defined edges in 2D images, based on Mumford–Shah functional for segmentation and level sets, is used for the detection of the aortic arch anatomy in a Phase-Contrast Magnetic Resonance Imaging (PCMRI) data. The segmentation strategy followed requires an initial contour extracted from the central image of the aortic arch, which is obtained from merging two initial structures; then, the initial contour is propagated to the adjacent images in order to segment all the images with aorta information. The results found suggest that the proposed approach represents a robust alternative for detection of the aorta anatomy in PCMRI data based on the 3D reconstruction from 2D segmentations.**

Key words—**Aorta segmentation, PCMRI, active contours, blood flow visualization.**

I. INTRODUCTION

Cardiovascular diseases (CVDs) are a group of disorders of the heart and blood vessels, such as diseases of the aorta and its branches, heart valve diseases, arrhythmia, among others. In general, CVDs refers to conditions that involve narrowed of or blocked blood vessels, which can lead to a heart attack or a stroke, reason why CVDs remain the biggest cause of deaths worldwide; therefore, early detection is key to improving outcomes of CVDs [1]. In order to better understand the mechanism of initiation and progression of a CVD as well as to assess the presence of a particular pathology condition, flow patterns studies should be integrated with a morphometric characterization, which consists in evaluating size (diameter or radius, area) and shape (curvature or tortuosity) of vessels [2].

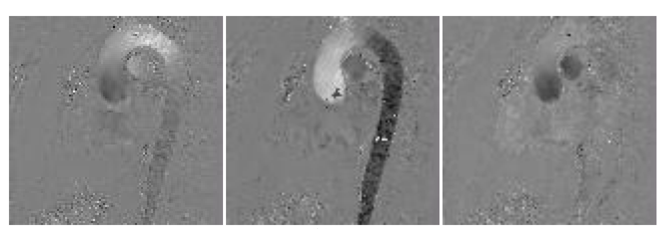
Magnetic Resonance Imaging (MRI) with Phase-Contrast velocity encoding (PCMRI) is a particular sequence able to acquire simultaneously anatomical and functional images. This technique, exploiting the observation that spins moving through a magnetic field have a phase shift proportional to their velocity, enables to acquire images of blood flow velocity during the heart beat cycle [3]. Also it is a well-assessed routine clinical tool for the evaluation of cardiac function and heart diseases, valve abnormalities, and vessel blood flow [4]. A PCMRI data consist of magnitude images, visualizing the subject's anatomy, and phase images composed of three volumes, each containing one of three velocity components: foothead (fh), right-left (rl), and anterior-posterior (ap) directions; these three images are acquired for each cardiac phase.

The main drawback of PCMRI data is its very low signal to noise ratio, which makes difficult a proper detection of borders from anatomical structures of interest, such as the aorta and their branches. In order to overcome this problem, we propose to use a segmentation technique known as Active Contours. There are many algorithms based on this technique, however many of them are not suitable for this kind of images because the stopping term depends on the gradient of the image (border of structures), which is not easy to handle with PCMRI data. The aim of this project is to segment the aorta and obtain information of the blood flow using a PCMRI-sequence by an active contours approach based on an algorithm proposed by Chan-Vese [5] that can detect not well-defined edges in 2D images. The outline of this paper is as follow. In section II, we describe briefly the PCMRI data acquisition, the theory of Active Contours, the aorta segmentation process followed, the 3D reconstruction method used, and the blood flow estimation process. Section III presents the results found, together with a brief discussion. Finally, in section IV, conclusions are drawn.

II. METHODS

A. Images Dataset

Images used in this work come from PCMRI data of the aortic arch of one healthy male subject that signed the informed consent form approved by an Institutional Review Board. The images were acquired using a MR Philips Achieva 1.5 T scanner. A T1-weighted cardiac-gated respiratory compensated 3D Phase Contrast Turbo Gradient Echo sequence was used. Repetition Time/Echo Time equal to 5.4/3.0 ms and a Velocity Encoding (VENC) value equal to 150 cm/s in all three space directions were adopted. The voxel size was 2 x 2 x 2 mm and the heartbeat was divided in 2 cardiac phases, systole and diastole. Because most of the blood flow occurs in the systolic phase, the present work focused in this particular images dataset; an example of the PCMRI data used is presented in Fig. 1.



(a) (b) (c)

Fig. 1. Example of PCMRI data in (a) anterior-posterior (ap), (b) foot-head (fh) and (c) left-right (lr) directions.

B. Active Contours Theory

In order to extract an anatomic model of the aortic arch, a segmentation process, based on an active contours approach proposed by [5], was used. This method detects objects in an image based on Mumford–Shah functional for segmentation and level sets [6]. This model can detect objects whose boundaries are not necessarily defined by gradient. In the level set formulation, the problem becomes a mean-curvature flow-like evolving the active contour, which will stop on the desired boundary. This model use calculus of variations and is characterized by start drawing a contour in the plane of the image. In this way, an initial segmentation is established and then the contour evolve according to some equation. The aim is to transform the contour so that it stops at the edges of the region to segment.

The goal of the segmentation algorithm is to minimize a functional F for a given image u_0, using the level set $\phi(x,y) = 0$ to segment objects of interest in u_0. Now, using the Heaviside function H, and the one-dimensional Dirac measure δ, as described in [5], the energy $F(c_1, c_2, \phi)$ can be written as:

$$
\begin{aligned}
&F(c_1, c_2, \phi) \\
&= \mu \int_{\Omega} \delta(\phi(x,y))|\nabla\phi(x,y)|\, dxdy \\
&+ v \int_{\Omega} H\big(\phi(x,y)\big) dy\, dx \\
&+ \lambda_1 \int_{\Omega} |u_0(x,y) - c_1|^2\, H\big(\phi(x,y)\big) dxdy \\
&+ \lambda_2 \int_{\Omega} |u_0(x,y) - c_2|^2 (-H(\phi(x,y))) dxdy \qquad (1)
\end{aligned}
$$

where $\mu \geq 0$, $v \geq 0$, and $\lambda_1, \lambda_2 > 0$ are parameters selected by the user to fit a particular class of images. The first term of the equation can be considered as a length penalization of the contour, so μ must be fixed depending on the characteristics of the objects in the image which are intended to segment, for example, if we have to detect only larger objects, and to not detect smaller objects (like points, due to the noise), then μ has to be larger. The second term is the area penalization of the segmented image, here v is a constraint on the área inside the curve that helps to increase the propagation speed. Finally, λ_1 and λ_2 weights and give importance to the region inside and outside of the boundary. Then, c_1 and c_2 are in fact given by:

$$
\begin{cases} c_1(\phi) = \text{average}(u_0) \text{in } \{\phi \geq 0\} \\ c_2(\phi) = \text{average}(u_0) \text{in } \{\phi < 0\} \end{cases} \qquad (2)
$$

Keeping ϕ fixed and minimizing the energy $F(c_1, c_2, \phi)$ with respect to the constants c_1 and c_2, it is easy to express these constants function of ϕ by:

$$
c_1(\phi) = \frac{\int_{\Omega} u_0(x,y) H\big(\phi(x,y)\big) dxdy}{\int_{\Omega} H\big(\phi(x,y)\big) dxdy} \qquad (4)
$$

$$
c_2(\phi) = \frac{\int_{\Omega} u_0(x,y)(1 - H\big(\phi(x,y)\big)) dxdy}{\int_{\Omega}(1 - H\big(\phi(x,y)\big)) dxdy} \qquad (5)
$$

Keeping c_1 and c_2 fixed, and minimizing F with respect to ϕ, we deduce the associated Euler–Lagrange equation for ϕ. Parameterizing the descent direction by an artificial variable time, the equation in $\phi(t,x,y)$ (with $\phi(0,x,y) = \phi_0(x,y)$ defining the initial contour) is:

$$
\begin{aligned}
\frac{\partial\phi}{\partial t} = \delta_{\varepsilon}(\phi) \Big[\mu \operatorname{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - v - \lambda_1(u_0 - c_1)^2 \\
+ \lambda_2(u_0 - c_2)^2\Big] = 0 \quad \text{in } (0,\infty) \text{ x } \Omega, \qquad (6)
\end{aligned}
$$

For the discretization of the equation in ϕ, a finite differences implicit scheme was used. Then, a linear system is obtained and can be solved by an iterative method. For more details, we refer the reader to [5].

C. Aortic Segmentation and Reconstruction

Observing the image sets with the information of velocity in the three different directions, we can notice that in fh images the aorta has better defined boundaries than rl and ap images. In these images (Fig. 1-b) it is possible to observe that the surface of the aorta is divided into two main regions: the ascendant aorta (clear zone) and the descendent aorta (dark zone). Hence, it was necessary to obtain a first segmentation from these two regions. Two initial contours were created, one for each region of the aorta and we set the value of μ to 1000 and 400 iterations. In this work, both values were calculated empirically. In this study we choose the parameters as follows: $\lambda_1 = \lambda_2 = 1, v = 0, h = 1$ (the step space), $\Delta t = 2$ (time step). We adjust the value of μ to 1000 because the noise in the images was considerably high [5].

Afterward, we use morphologic operations to improve and merge these two contours [7]. First, we applied an erosion process to eliminate the sites that did not belong to the aortic surface and then we use a dilatation process to recover the area, in both cases a disk was used as structuring element with a radius of 2 pixels. Finally, the union of both segmented regions of the aorta were merged to obtain one unique surface represented as a binary mask. Then, this binary mask was used as an initial contour for the upper and lower adjacent images. We repeat this process until all images were segmented.

In addition, to corroborate that the segmentations obtained from the studied method correspond properly to the anatomy

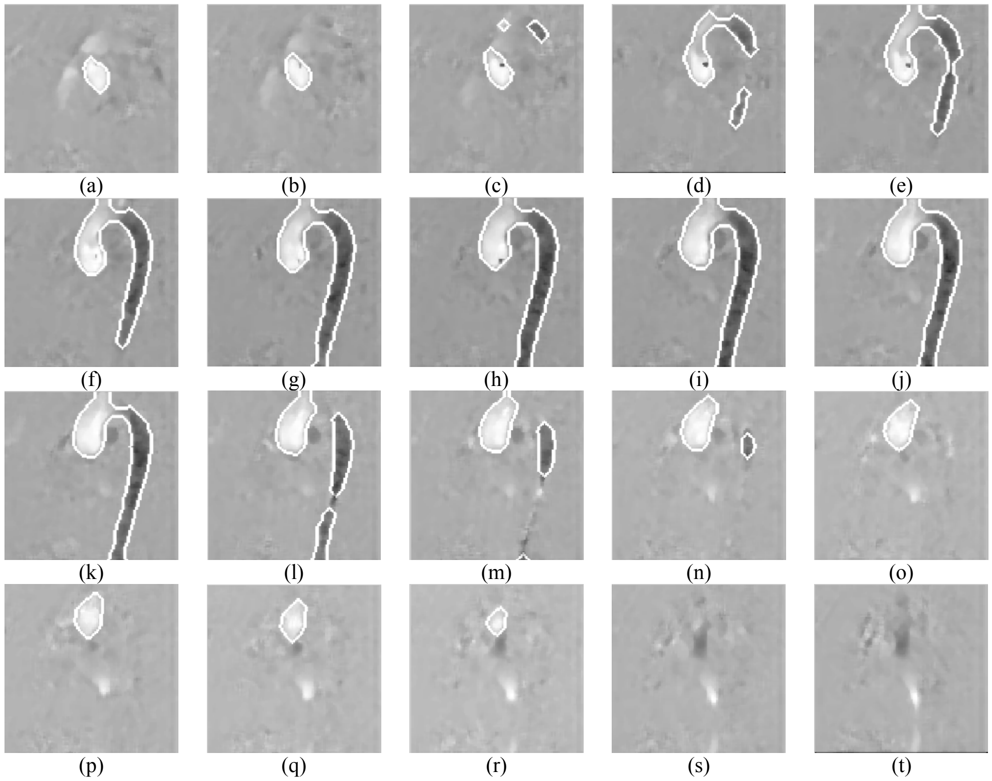


Fig. 2. PCMRI fh dataset with the corresponding aorta segmentation (white contour) on each image.

of the aortic arch, a regular 3D reconstruction was performed in MatLab®.

D. Aortic Blood Flow

A 3D reconstruction of the blood flow was also performed, it was carried out using the obtained segmentation in fh direction to conserve the useful information in the PCMRI volumes (fh, rl and ap), and thus obtain the magnitud and direction of the flow inside the aorta. Now, since all the voxel values are positive, it was necessary to substract the mean gray value in such a way that it was possible to detect positive values which indicate upward direction and negative values which indicate downward direction. Having done this normalization, we used the Matlab® function *coneplot* being possible to display cones indicating the flow direction within the aorta segmented anatomy.

For a better understanding of the methodology studied in this paper, we propose a strategy that can be summarize in the next steps:

1. *Apply a median filter,* before segmentation, in order to eliminate noise from the images preserving the edges [8].
2. *Create two initial contours*, with no specific form that could be used as initialization for the central image.
3. *Segment two regions from the central image*, corresponding to the ascending and descending aorta regions.
4. *Merge both segmented regions*, by applying morphological operations (erosion followed by a dilatation process).
5. *Segment adjacent images*, using the segmentation obtained in the previous step as the input contour for the adjacent images.
6. *Segmentation of all the images*, by propagating the contours obtained in step 5 to their respective adjacent images, until reaching the first and last slide from the image dataset.
7. *Perform a 3D reconstruction*, using all the obtained 2D segmentations.
8. *Graph blood flow,* taking the information of the segmented area in all three directions.

III. RESULTS AND DISCUSSION

A. Aorta Segmentation

In Fig. 2, the results obtained by segmenting the entire set of fh systolic PCMRI images following the proposed strategy are presented, where is possible to observe, for each image, a white contour corresponding to the aorta section in each 2D slide; in this images is also possible to observe how each segmentation properly fits the aorta. Fig.2 (s) and Fig.2 (t) are the exception because no contours are shown in these two slides due to absence of aorta information, even if these images belong to the fh

(a) (b)

Fig. 3. (a) 3D reconstruction of the aortic arch from the 2D segmentations of the PCMRI data, (b) Blood flow in the aortic arch.

images dataset, suggesting that the active contours method is capable to properly track the regions of interest by the propagation of the contours.

B. Aorta 3D Reconstruction and Blood Flow

Fig. 3 (a) shows the result of the volumetric reconstruction of the aortic arch using the set of 2D segmentations obtained from the studied methodology. In this figure is easy to observe that the achieved segmentations are adequate due to the proper form of the obtained surface representing the aortic arch.

In Fig. 3 (b), we can visualize the blood flow obtained from the information in fh, ap and rl volumes and the segmentation found before. Here is possible to observe that the blood flow is stronger in the ascending aorta and aortic arch than the descending aorta; this is because the PCMRI was acquired at the beginning of the systole. It is also important to note the details that can be appreciated in these images, since we can observe the flow going to the brachiocephalic trunk in the upper part of the aortic arch.

IV. CONCLUSIONS

The active contours approach based on the Mumford–Shah functional and level sets provided an acceptable segmentation of the aorta in PCMRI images; and because of its robustness to the initialization this method could represent a useful tool for the segmentation of different anatomical structures of interest presented in noisy images, and could be used as an alternative for the representation of 3D structures constructed from a set of 2D regions.

The blood flow obtained shows the expected results, it can be appreciated a consistent flow in each section of the aorta, including the branches at the top of the arch.

As future work, this approach will be compared with state of the art segmentation algorithms that works in 3D in order to assess its accuracy and speed, and also if the obtained segmentation in this work could be used as initialization to help improve the accuracy of more complex segmentation algorithms. Also, we pretend to calculate quantitatively the blood flow in the aorta during the entire cardiac cycle (systole and diastole), that can be achieved using the segmentations obtained and the gradients of PCMRI. To achieve the quantification of blood flow in the aorta, we will develop an analysis with 2D planes that would be positioned in different regions of the artery, and in this way use the image data to calculate peak and mean velocities and flow. Further, evaluate and compare the presented blood flow approach with other methods that allow a better visualization of the blood flow during all the cardiac cycle will be studied.

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