Toward an Automatic Left Atrium Localization Based on Shape Descriptors and Prior Knowledge

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Abstract. The left atrium is one of the four chambers of the heart. It receives oxygenated blood from the lungs and pumps it into the left ventricle. This blood is then circulated to the rest of the body. In a healthy adult the left atrium pumps blood into the ventricle in a regular rhythm. In atrial fibrillation (AF), the left atrium quivers in an abnormal rhythm and is no longer able to pump blood into the left ventricle efficiently. On the other hand MRI and CT are commonly used for imaging this structure. Segmentation can be used to generate anatomical models that can be employed in guided treatment and also more recently for cardiac biophysical modelling. For this reason, segmentation of the left atrium is a task with important diagnostic power. In this paper, we propose an automatic localization method in order to detect the left atrium in MRI images. Our method is based on shape descriptor and prior knowledge. For this purpose some descriptors are selected: circularity, area, the center of mass of each region, elongation factor, type factor. We propose also to use some prior knowledge as pulmonary artery position, and the left atrium position.

Keywords: Left atrium, shape descriptors, prior knowledge, localization.

1 Introduction

Cardiovascular diseases are the most common causes of deaths in the word. Heart strokes and attacks are two pathologies that affect the left atrium. The American Heart Association reports that 15% of all heart strokes are caused by a life threatening condition called atrial fibrillation (AF) [1].

Recently, a number of segmentation algorithms have been developed to detect LA in MRI or CT images.

For example in[2]the authors present a semi-automatic approach for left atrium segmentation and the pulmonary veins from MR angiography (MRA) data sets. They also propose an automatic approach for further subdividing the segmented atrium into

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the atrium body and the pulmonary veins. The idea of this segmentation algorithm is that in MRA images the atrium becomes connected to surrounding structures via partial volume affected voxels and narrow vessels, thus the atrium can be separated if these regions are characterized and identified. The blood pool, obtained by subtracting the pre- and post-contrast scans, is segmented using a region growing approach and subdivided into disjoint subdivisions on the basis of the of the Euclidean distance transform. These subdivisions are then merged automatically starting from a seed point and stopping at the points where the atrium leaks into a neighbouring structure. The resulting merged subdivisions produce the segmented atrium. As second technique they propose an automatic approach used to identify the atrium body from segmented left atrium images. The separating surface between the atrium body and the pulmonary veins gives the ostia locations and can play an important role in measuring their diameters.

Another automatic approach for LA segmentation on cardiac magnetic resonance images was presented in [3]. This method used a weighted voting label fusion and a variant of the demons registration algorithm adapted to handle images with different intensity distributions to segment LA. In another paper[4], Yefeng et al. have proposed a segmentation approach applied toun-gated C-arm CT, where thin boundaries between the LA blood pool and surrounding tissues are often blurred due to the cardiac motion artifacts. The segmentation of this kind of images presents a big challenge compared to the highly contrasted gated CT/MRI. To avoid segmentation leakage, the shape prior was exploited in a model based approach to segment LA parts. However, independent detection of each part was not optimal and its robustness needs further improvement (especially for the appendage and PVs). So, they proposed to enforce a statistical shape constraint during the estimation of pose parameters (position, orientation, and size) of different parts. In[5]the authors present a method used to extract heart structures from CT and MRA data sets, in particular the left atrium. First, the segmented blood pool was subdivided at narrowings in small components. Second, these basic components were merged automatically so that they represent the different heart structures. The resulting cutting surfaces have a relatively small diameter compared to the diameter of the neighboring heart chambers. Both steps are controlled by only one fixed parameter. The method was presented as being fast and allowing interactive post-processing by the user.

Other authors in [6] proposed to use shape learning and shape-based image segmentation to identify the endocardial wall of the left atrium in the delayed-enhancement magnetic resonance images.

Some other works in the literature exploit a prior shape of the LA (either in the form of an atlas [7,8] or a mean shape mesh [9]) to guide the segmentation process. For example, Manzkeet al. [9] built a mean shape of the combined structure of the LA chamber and PVs from a training set. With a prior shape constraint, they could avoid the leakage around weak or missing boundaries, which plagues the non-model based approaches.

In this paper, we present a new approach to detect left atrium in MRI images. Our method is based on shape descriptors and prior knowledge.

2 Methodology

2.1 Left Atrium Localization

This section focuses on left atrium localization. To achieve this goal we propose the following algorithm:

- Threshold the original image: we start with a preliminary thresholding operation. The threshold value for each case is set empirically.
- Choose a slice where left atrium and aorta have circular shape.
- Process the binary image obtained: remove small regions, fill holes, separate objects.
- Characterization with shape descriptors: circularity, elongation, area, center of masse X, center of masse Y.

3 Characterization of the Left Atrium

A characterization step is essential to identify the regions of interest in cardiac MRI images. In the field of pattern recognition, we can find a large number of descriptors. The choice of an appropriate one depends on the object to be characterized. For some slices, the left atrium and the pulmonary artery have a generally circular shape and the left atrium is under the pulmonary artery, for this reason we chose the following attributes:

Perimeter of the Region P (R): This descriptor is calculated as the sum of the distances between successive contour pixels.
A (R): Area of the region.

Heywood Circularity Factor: $\boldsymbol{FcH} = P(R)/(2\sqrt{\pi.A(R)}$ (1)

Rectangularity: Is defined by the value R calculated by the following formula,
R= Object area/ area of the minimum rectangle supervision (RME),

Elongation Factor: Is defined by the following formula,= **EF= RME length / width of RME**

Type Factor:= Is a complex factor that relates the area to the moment of inertia.

$$F_t = \frac{A^2}{4\pi\sqrt{I_{xx}+I_{yy}}} \quad (2)$$

- M_x Center of masse X $\frac{(\sum x)}{A}$
- M_y Center of masse Y $\frac{(\sum y)}{A}$
- Moment of inertia: $I_{xx} = (\sum x^2) - A * {M_x}^2$
- Moment of inertia: $I_{yy} = (\sum y^2) - A * {M_y}^2$

4 Results and Discussions

To evaluate the influence of these parameters, we selected 20 images (10 from training data and 10 from test data). For each image, we applied morphological operators like border rejection and elimination of smalls regions.

On the other hand, we can see clearly that the left atrium is great than the pulmonary artery, and it is always at the bottom. So the center of the left atrium is at the bottom of the center of the Pulmonary artery. After the binarization, we estimate the center of masse X, center of masse Y, the factor type, Heywood Circularity factor, elongation factor and area. Above

Table 1 and 2 show the min, max values and the standard deviation for the parameters defined above for 20 images selected (10 from training and 10 from test)

Table 1. The min, max value and standard deviation for the LA

	Center of masse X	Center of masse Y	Area	Elongation factor	Heywood Circularity	Type factor
min	161.25	140.17	378	1.70	1.04	0.93
max	213.29	197.83	3054	2.72	1.33	0.98
STD	**15.27**	**16.64**	**623.27**	**0.28**	**0.07**	**0.02**

Table 2. The min, max value and standard deviation for the PA

	Center of masse X	Center of masse Y	Area	Elongation factor	Heywood Circularity	Type factor
min	149.39	111.71	183	1.55	1.00	0.88
max	214.38	155.47	865	2.33	1.17	0.99
STD	**15.67**	**11.34**	**149.84**	**0.22**	**0.07**	**0.03**

We notice from table 1 and 2 that the left atrium has an area greater than the PA. On the other hand, the PA has a circular shape. Indeed, the Heywood Circularity factor values are between the values 1 and 1.28, and the factor type value are generally greater than 0.93. On the basis of these results and using the position of the LA and PA we have proposed our algorithm presented in section 2 described above. We illustrate in figure 1 some results for patients: A002 slice 87, patient A001 slice 51 and patient A004 slice 83.

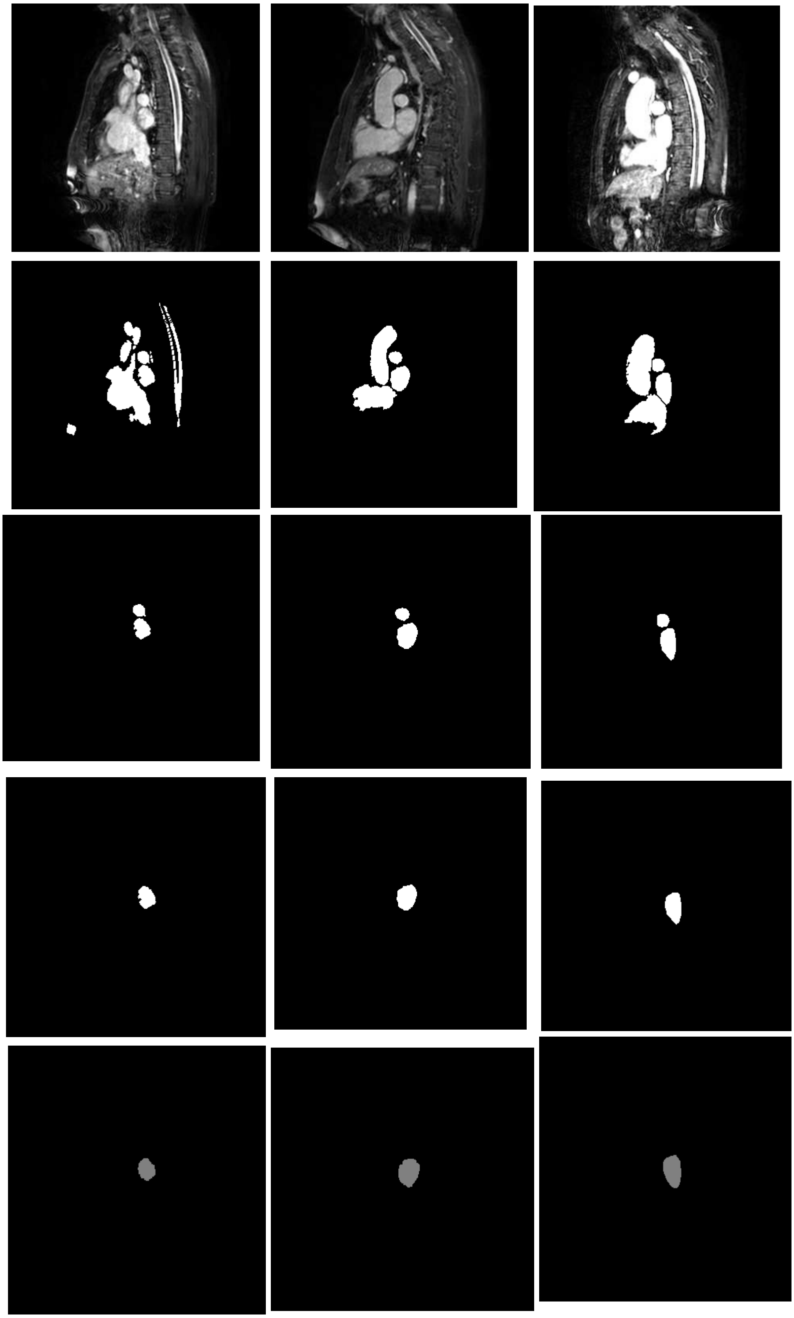

Fig. 1. Examples of segmentation and localization of LA using the proposed method: first line 3 MRI images. Second line : binarization. Third line: processing of the binary images in order to keep only LA and PA based on circularity index. Fourth line : LA detected. Fifth line: Ground truth segmentations.

We present also in figure 2 an example from test data: B002 slice 93

Fig. 2. Example of segmentation and localization of LA using the proposed method

For the 3D segmentation we use the center of mass of the LA detected to define a ROI around this center in order to localize the LA atrium in the next and previous slices.

5 Conclusion

We have presented in this paper a simple method used to localize the left atrium. The proposed algorithm was based on a preliminary threshloding and some morphological operations. In order to detect the left atrium we used some shape descriptors as position, area and circularity.

Our method was applied on the slices where the pulmonary artery has a circular shape. Once the PA artery is detected we localize the left atrium using the center of mass of X and Y.

For the others slices, we propose to use the center of gravity detected on the selected slice to search for the LA atrium region in previous and next slices.

At the moment the propose algorithms are not fully automatic because the threshold method provides sometimes bad results. That is why; we propose to combine in a future work the proposed detection method with a segmentation approach more efficient.

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