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FACTORS AFFECTING THE LEVEL SET SEGMENTATION OF THE HEART VENTRICLES IN SHORT AXIS CARDIAC PERFUSION MRI IMAGES

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INTRODUCTION

Cardiovascular diseases (CVDs) are the class of diseases related to heart and blood vessels such as: Coronary heart disease, Stroke, Cardiomyopathy, etc. CVDs cause 31% of the death rate globally [1]. Though, an international increase in the focus and awareness for the need of early diagnosis procedures. Cardiac Magnetic Resonance Imaging (CMR) has been widely adopted to diagnose CVD patients' in clinical routine. It provides high-resolution imaging and clear tissue contrast in addition to avoiding the exposure to the ionizing radiation. Perfusion CMR includes the injection of a special dye, often called contrast agent, during the scan in order to highlight the blood pool when good blood supply reaches it, which increases the contrast between muscle and blood pool [2].

Automatic segmentation is affected by all preceding preprocessing and initializations. In this study, we will focus our study on the effect of the registration and the active contour initialization on the accuracy of the ventricles segmentation task. The left ventricle (LV) segmentation meets lots of challenges due to the huge variation in size and shape of the LV, the heart contraction, the motion artifacts as well as the effect of papillary muscles. The RV segmentation is considered more challenging than the LV as it suffers from the complex crescent structure, wall irregularities, inhomogenenity and its ill-defined borders [3].

Several techniques are proposed to perform cardiac segmentation using active contour. Pluempitiwiriyawej et.al [4] introduced an automatic initialization approach for the myocardium segmentation, based on thresholding and morphological operations. Weijia et al [5] proposed a scheme for automatic close to boundary initialization for deformable models. They generate the initial contour through a labeling/recognition process using Topographic Independent Component Analysis (TICA) learning and feature exaction technique. Wu et al [6] improved the LV segmentation accuracy by adding a circle-shape based term to the active contour energy function, representing the LV shape. Li et.al [7] proposed a distance regularization term for the level set algorithm in order to maintain the regularity of the level set function during its evolution. Khalifa et al. [8] proposed al framework based on registration and level set method to segment the LV, based on the affine-based registration followed by a local B-splines based alignment, to account for local and global motion of the heart.

Motivated by the challenges in the initialization and registration on segmentation accuracy, we propose studying the effect of these tasks on the ventricles segmentation tasks. This study is achieved through developing a modified workflow to automatically segment the LV and RV using level set method. The use of level set theory has provided more flexibility and convenience in the implementation of active contours. To the best of our knowledge the RV segmentation was not studied for perfusion MRI due its difficulty.

MATERIAL AND METHODS

<u>Datasets</u>

Two CMR perfusion datasets have been used for the segmentation performance evaluation in this study. The datasets were acquired using the Gradient Recalled-Echo (GR) MR scan protocol. It consists of 10 image sequences. Each sequence is formed of 3 slices named; Basal, medial, and apex for different time frames ranged between 32 and 101 time frame.

Methodology

Our study consists of five main steps: Preprocessing, Heart Localization, Initial Contour Extraction, Registration, and Segmentation.

Preprocessing and localization step

The aim of the preprocessing step is to enhance the image quality without affecting image details. Gaussian filter was used, as the MRI imaging related noise can be assumed to follow the Gaussian distribution [9]. The localization step is the process of find the heart region in the image. In this study, we will use the Circular Hough transform based localization algorithm to localize through searching for the LV as well as the RV[10].

Initial contour extraction

To the best of our knowledge, most of the segmentation algorithms in the literature use a circular or elliptic shape in the center of the slice as the initial contour for the LV [3,4,6]. Nevertheless, these assumptions will fail since most of the time especially in case of diseased LV muscles. In addition, it is considered an inappropriate assumption for RV shape as shown in Fig 1. Therefore we propose finding an initial contour that reflects roughly the shape, size and position of the heart related to each slice. The proposed algorithm can be summarized as follows:

1- The intensity time curve, shown in Fig 2, is calculated for the ROI selected by the localization step for each slice.

The intensity time curve is defined as the average high intensities in each time frame, the high intensity is defined as the intensity greater than the threshold (T) calculated as the maximum of threshold calculated based on Otsu' method and intensity value calculated at 80% of the area under intensity probability density function curve.

2- The best frame is selected from the intensity time curve through sorting the peaks of the first one third of the cardiac cycle.

The peaks of the intensity time curve reflect the frames with high intensities due to the maximum filling of the contrast agent in RV and LV respectively, occurring at the first one third of the cardiac cycle. Therefore, the best frames to extract the initial contour for both RV and LV respectively are founded in this period.

3- The selected frame is converted from gray level to binary image using the threshold T.

4- Finally, a series of morphological operations (opening, closing) were used to remove unwanted pixels. The initial contour extracted is the contour of remaining object as shown in Fig 3.

Registration step

It is the process of aligning all time frames to the automatically selected reference frame for each slice. Though, two different registration algorithms were studied, to highlight the effect of the registration on the accuracy of segmentation. For simplicity, the translational transformation is the only studied, based on both spatial and frequency domains.

The frequency based registration is mainly calculating the Fourier shift between 2 images corresponding to that in the spatial domain, which is represented formed as a linear phase difference. Though, the phase correlation between two images I_1 and I_2 can be defined as the normalized cross power spectrum between A and B as in the following equation:

$$Q(u,v) = \frac{A(u,v)B^*(u,v)}{\left|A(u,v)B^*(u,v)\right|}$$

where A, B are the Fourier transform of I_1 and I_2 respectively [11].

Segmentation using active contour

The aim of segmentation is to extract the LV and RV using the level set algorithm [12]. This algorithm requires a well localized initial contour in order to accurately and rapidly perform the segmentation task.

Contour initialization

In our study, we will investigate 2 different methodologies for the contour initialization process to study their effect of on the segmentation accuracy. The first initialization is

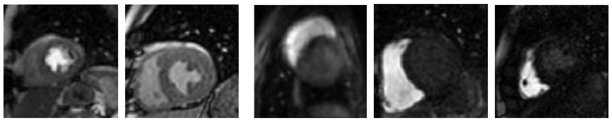

Figure 1: different shapes for (a) - (b) LV, and (c) - (e) RV.

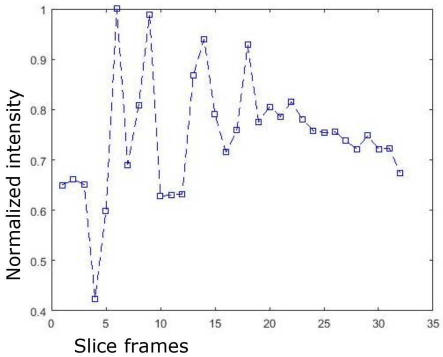

Figure 2: Intensity time curve.

Figure 3: Initial contour extraction steps for LV. (a) original image, (b) after threshold, and (c) initial contour in red.

considering the previously extracted contour from each slice is considered as the starting initial contour for this slice. In addition, the final contour segmented for any time frame is considered as the initial contour for the next frame. In the second initialization algorithm, we propose defining initial contour for each frame based on the image's polar representation. The algorithm can be defined as follows:

1- Transforming each Cartesian frame into the polar coordinates representation where the center of transformation is calculated from the previously extracted initial contour.
2- Converting the gray level polar coordinates image to a binary image using a threshold T value for the LV and T_1 value for the RV.

Where T_1 is the average value of threshold using Otsu' method and intensity value at 80% of the area under probability density function curve.

3- Keeping objects found in the upper first third of the binary image. As transformation process makes the LV region at top third of the image (approximately the height of LV to image height). This step used only for LV.
4- Transform the image back to Cartesian coordinate, where the contour of survived object is considered as the initial contour of this frame as shown in Fig.4.

Level set method

After obtaining the initial contour, we use the Distance Regularized Level Set Evolution (DRLSE) for the segmentation task. It allows the use of relatively large time steps to significantly speed up curve evolution, while ensuring adequate numerical accuracy [7].

Evaluation metrics

In order to evaluate the performance of segmentation we used the: Dice metric, and Hausdorff distance to compare the segmented contour to experts segmented contour [13].

RESULTS AND DISCUSSION

The performance of the proposed method was tested using dataset of short axis CMR perfusion images.

The different registration algorithms effect on the segmentation of LV and RV is shown in table 1, and table 2 respectively. The use of straightforward translation concept in image domain gives better result than that in the frequency domain using phase correlation method. The phase correlation is highly affected by image noise as it produces high peaks in Fourier transform images. In order to improve this results Gaussian filter was used to smooth the Fourier image. This process still failed to succeed in registering some frames, so it degrades the overall segmentation accuracy. The difference in accuracy due to effect of registration is about 5%, and 9% for LV and RV respectively.

Table 3 and table 4, shows the effect of the initialization to level set method using the previously extracted contour and polar based initialization algorithms on the performance of the segmentation of the LV and RV respectively. From results, we can conclude that the segmentation accuracy is affected by the initialization process. Changing the initialization method affect the accuracy of segmentation by factor of 4% and 1% when applied for the segmentation of LV and RV respectively. The polar based method improves the result trough extracting initial contour for each frame instead of taking it from the previous frame as done in the literature.

Figure 4: Initialization steps for LV. (a)original image, (b)image in polar, (c)after threshold, (d)after processing, (e)image back to Cartesian, and (f)initial contour in red.

Table1: effect of registration on LV segmentation

	Slice level	DM	HD
Reg. 1	**Base**	0.89 ± 0.08	5.77 ± 3.24
	Mid	0.73 ± 0.08	9.10 ± 2.49
	Apex	0.70 ± 0.13	5.69 ± 2.25
Reg. 2	**Base**	0.84 ± 0.14	7.40 ± 5.49
	Mid	0.75 ± 0.10	8.54 ± 3.49
	Apex	0.58 ± 0.12	13.80 ±4.18

Table 2: effect of registration on RV segmentation

	Slice level	DM	HD
Reg. 1	**Base**	0.86 ± 0.06	10.24 ±3.06
	Mid	0.77± 0.09	10.03 ±2.86
Reg. 2	**Base**	0.80 ± 0.08	11.29 ±4.51
	Mid	0.59 ± 0.12	13.70 ±3.84

Table 3: effect of initialization on LV segmentation

	Slice level	DM	HD
Initial. 1	**Base**	0.89 ± 0.08	5.77 ± 3.24
	Mid	0.73 ± 0.08	9.10 ± 2.49
	Apex	0.70 ± 0.13	5.69 ± 2.25
Initial. 2	**Base**	0.88 ± 0.10	6.79 ± 4.10
	Mid	0.81 ± 0.09	7.00 ± 2.66
	Apex	0.75 ± 0.13	5.04 ± 2.30

Table 4: effect of initialization on RV segmentation.

	Slice level	DM	HD
Initial. 1	**Base**	0.86 ± 0.06	10.24 ± 3.60
	Mid	0.77 ± 0.09	10.03 ± 2.86
Initial. 2	**Base**	0.84 ± 0.09	12.50 ± 6.48
	Mid	0.80 ± 0.10	8.83 ± 3.78

CONCLUSION

In this work we study, the effect of the registration and contour initialization of the cardiac ventricles segmentation using level set method. The workflow starts with image denoising, heart localization, followed by the registration, contour initialization, segmentation and finally, the performance evaluation. The segmentation accuracy improved, through using registration in image domain algorithm, by 5%, and 9% for LV and RV segmentation respectively. While improved, trough using polar based initialization algorithm, by 4%, and 1% for LV and RV segmentation respectively.

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