A Novel Level Set Method for Segmentation of Left and Right Ventricles from Cardiac MR Images

Yu Liu, Chunming Li, Shuxu Guo, Yihua Song and Yue Zhao

Abstract—**In this paper, we propose a novel level set method for segmentation of cardiac left and right ventricles based on the distance regularized level set evolution (DRLSE) framework [7] and the distance regularized two-layer level set (DR2LS) model [17]. First, DRLSE is applied to obtain a preliminary segmentation of left and right ventricles, which is then used to initialize the endocardial contour, which is represented by the zero level contour of the level set function in our method. Then, the epicardial contour is represented by a different level contour of the same level set function. These two level sets are optimized by an energy minimization process to best fit the true endocardium and epicardium. In order to ensure smoothly varying distance between the two level contours, we introduce a distance regularization constraint in the energy function. With the region-scalable fitting (RSF) energy [8] as the data term, our method is able to deal with intensity inhomogeneities in the images, which is a main source of difficulty in image segmentation. Our method has been tested on cardiac MR images with promising results.**

I. Introduction

Segmentation of cardiac left ventricle (LV) and right ventricle (RV) plays an important role in non-invasive assessment of ventricular function [1][13]. The evaluation of clinical parameters demands for cardiac ventricles segmentation, which have been used to obtain ventricular stroke volume, cardiac output and ejection fraction. These important measurements are all computed from the ventricle segmentation results.

Manual LV and RV segmentation in clinical routine is a time consuming and tedious task, which is performed without using three-dimensional information [13]. In order to reduce workload and drawbacks of manual segmentation, many groups have developed automated segmentation methods. Automatic segmentation of LV and RV is still an open problem, although there have been many algorithms proposed to address this problem [2][3]. The low contrast between tissues surrounding the epicardium and image artifacts, including intensity inhomogeneities in MR images, is main challenge in LV and RV segmentation.

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Some of these researchers have applied traditional segmentation methods, for example, thresholding, classification, region-growing, clustering, to segment cardiac images [2][4][14]. Others have used active shape models and active appearance models that introduce statistical shape templates as prior knowledge [1][5]. Another promising approach to segment images using prior knowledge is known as atlas-based segmentation [6]. But the quantity and variety of images in the training set impair the segmentation quality of these methods seriously.

Level set methods have been used to segment cardiac ventricles [10]. A multilayer level set segmentation method was proposed by Chung and Vese using multiple level sets of one level set function to fit object boundaries [9]. However, this method has not been shown effective for segmenting cardiac ventricle. Moreover, there is no constraint on the distance between different level contours in their method and even none of the above-mentioned algorithms have ability to deal with intensity inhomogeneities in the images.

In this paper, we use distance regularized level set evolution to obtain a preliminary segmentation of left and right ventricles, which is then used to initialize endocardial contour represented by the zero level contour of the level set function. Then a two-layer level set formulation is applied for segmenting ventricles of cine cardiac MR short-axis images. A distance regularization constraint on the level contours is used to preserve the anatomical structures of the LV and RV. We also draw a data term into energy formulation to overcome intensity inhomogeneities of images [8].

We organize the remainder of this paper as follows. Our proposed level set function is introduced in section II. Experiments and results are shown in section III. Section IV and V deal with the discussion and conclusion, respectively.

II. Method

A. Preliminary segmentation of left and right ventricles using DRLSE

In our method, we use distance regularized level set evolution (DRLSE) to obtain a preliminary segmentation of left and right ventricles, which is used to define the initial level set function for the distance regularized two-layer level set (DR2LS) model described in Section II-B. The DRLSE formulation is described as follows. For an level set function $\phi: \Omega \to \Re$, an energy function $\mathcal{E}(\phi)$ is defined as

$$\mathcal{E}(\phi) = \mu\mathcal{R}(\phi) + \lambda\mathcal{L}_g(\phi) + \alpha\mathcal{A}_g(\phi) \tag{1}$$

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where μ, λ and α are the coefficients of the energy functional $\mathcal{R}(\phi), \mathcal{L}_g(\phi)$ and $\mathcal{A}_g(\phi)$, respectively. $\mathcal{R}(\phi), \mathcal{L}_g(\phi)$ and $\mathcal{A}_g(\phi)$ are defined as

$$\mathcal{R}(\phi) \triangleq \frac{1}{2}(|\nabla\phi| - 1)^2 dx \tag{2}$$

$$\mathcal{L}_g(\phi) \triangleq \int_\Omega g\delta(\phi)|\nabla\phi| dx \tag{3}$$

$$\mathcal{A}_g(\phi) \triangleq \int_\Omega gH(-\phi)dx \tag{4}$$

with an edge indicator function g

$$g \triangleq \frac{1}{1+|\nabla G_\sigma * I|^2} \tag{5}$$

where δ is the Dirac delta function and H is the Heaviside function. ∇G_σ is a Gaussian kernel with a standard deviation σ. The energy $\mathcal{R}(\phi)$ is the regularization term. The energy $\mathcal{L}_g(\phi)$ computes the line integral of the function g along the 0-level contour of the level set function ϕ. $\mathcal{A}_g(\phi)$ is introduced to speed up the motion of the 0-level contour in the level set evolution process by expanding and shrinking of the region enclosed by the 0-level contour.

In practice, the Dirac delta function δ and H are approximated by the smooth function $\delta_\varepsilon(x)$ and $H_\varepsilon(x)$, which are defined by

$$\delta_\varepsilon(x) = \begin{cases} \frac{1}{2\varepsilon}\left[1 + \cos(\frac{\pi x}{\varepsilon})\right], & |x| \le \varepsilon \\ 0, & |x| > \varepsilon \end{cases} \tag{6}$$

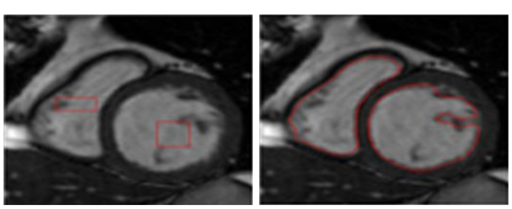
and

$$H_\varepsilon(x) = \begin{cases} \frac{1}{2}\left(1 + \frac{x}{\varepsilon} + \frac{1}{\pi}\sin\left(\frac{\pi x}{\varepsilon}\right)\right), & |x| \le \varepsilon \\ 1, & x > \varepsilon \\ 0, & x < -\varepsilon. \end{cases} \tag{7}$$

Energy can be minimized by solving the following gradient flow:

$$\frac{\partial\phi}{\partial t}(\phi) = \mu[\nabla^2\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)] + \lambda\delta_\varepsilon(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + \alpha g\delta_\varepsilon(\phi). \tag{8}$$

Interested readers are referred to [7] for the original formulation of the DRLSE model.



(a) (b)

Figure 1: Initialization using distance regularized level set evolution, DRLSE. *(a) initialization for DRLSE, (b) final zero level of DRLSE used as the initialization of two-layer level set function.*

For example, we show the initial and final contours of the DRLSE model in Fig. 1(a) and 1 (b), respectively. The final contour of the DRLSE model in the first step is used as the initial endocardial contour in the next step described below.

B. Distance regularized two-layer level set method

The second step of our method aims to refine the endocardial contour obtained in the first step, as shown in Fig. 1(b), and obtain the epicardial contour at the same time. In this step, we incorporate the anatomical knowledge of the heart in our two-layer level set formulation, in which the endocardial and epicardial contours are represented by two specified level contours of one level set function.

The endocardium is a silky membrane that lines the cavities of heart and the valves [10]. The thick layer of cardiac muscle is myocardium which is used for the shrink and extension of the ventricles. A thin layer outside of the myocardium is called the epicardium, which consists mostly of connective tissue and fat [10][11]. This anatomical knowledge can be reflected in the following two-layer level set representation of endocardial and epicardial contours. As shown in Fig. 2, in our two-layer level set function, we use 0-level and k-level contours, denoted by C_0 and C_k, to represent the endocardium and epicardium, respectively. Moreover, in the light of the geometric properties of endocardium and epicardium, the optimal level set equation should meet the following two properties: 1) the two level contours are as smooth as possible; 2) the distance between the two level contours is smoothly varying.

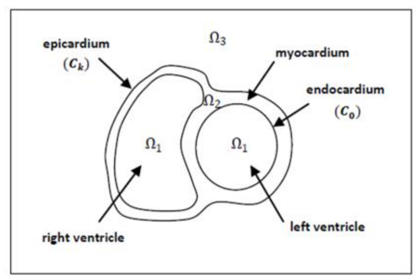


Figure 2: The representation of endocardium and epicardium of left ventricle and right ventricle in level set function.

With the above two-layer level set representation of endocardial and epicardial contours, we define an energy functional for a level set function with

$$\mathcal{F}(\phi) = D(\phi) + \mathcal{E}(\phi) + \mathcal{L}(\phi) \tag{9}$$

where D is the distance regularization term, $\mathcal{E}$ is the data term, and $\mathcal{L}$ is the contour regularization term. The distance regularization term D is introduced to keep the distance of two contours smoothly varying. The data term $\mathcal{E}$ is able to catch object boundaries in the presence of intensity inhomogeneities, which is derived from the region-scalable fitting (RSF) model proposed in [8]. The contour regularization term $\mathcal{L}$ makes sure that the two level contours are smooth.

The energy term D in (9) is defined as

$$D(\phi, \alpha) = \mu\int\frac{1}{2}\left(|\nabla\phi(\mathrm{x})| - \alpha(\mathrm{x})\right)^2 d\mathrm{x} + \omega\int|\nabla\alpha(\mathrm{x})|^2 d\mathrm{x} \tag{10}$$

where μ > 0, ω > 0 are used as weighting coefficients. In term D, $|\nabla\phi(\mathrm{x})|$ can be forced to be a function $\alpha(\mathrm{x})$. Meanwhile, $\alpha(\mathrm{x})$ can be kept smooth d ue to the second term. This energy is called distance regularization term, and its effect is to keep distance between 0-level and k-level contours smoothly varying.

We define local intensity clustering energy $\mathcal{E}_y$ as

$$\mathcal{E}_y = \sum_{i=1}^{3} \lambda_i \int K_\rho(\mathrm{x}-\mathrm{y})|I(\mathrm{x}) - f_i(\mathrm{y})|^2 M_i(\phi(\mathrm{x}))dx \quad (11)$$

with

$$M_i(\phi(\mathrm{x})) = \begin{cases} 1, & \mathrm{x} \in \Omega_i \\ 0, & \mathrm{x} \notin \Omega_i \end{cases},$$

$$K_\rho(\mu) = \begin{cases} a, & for\ |u| \le \rho \\ 0, & for\ |u| > \rho \end{cases},$$

where λ_i is the weighting coefficient and $\Omega_1 \triangleq \{\mathrm{x}: \phi(\mathrm{x}) < 0\}, \Omega_2 \triangleq \{\mathrm{x}: 0 < \phi(\mathrm{x}) < k\}, \Omega_3 \triangleq \{\mathrm{x}: \phi(\mathrm{x}) > k\}$ as shown in Fig.2, represent cavity, myocardium and zone outside the epicardium, respectively. K_ρ is a nonnegative kernel function.

We minimize the integral of $\mathcal{E}_y$in (11), with respect to the neighborhood center y, and obtain the energy function:

$$\mathcal{E}(\phi, f_1, f_2, f_3) = \int \mathcal{E}_y\, d\mathrm{y}$$

$$= \sum_{i=1}^{3} \lambda_i \int\int K_\rho(\mathrm{x}-\mathrm{y})|I(\mathrm{x}) - f_i(\mathrm{y})|^2\, M_i(\phi(\mathrm{x}))dy\,. \quad (12)$$

We can overcome intensity inhomogeneities in cardiac MR images by using this energy term for segmenting ventricles. The original formulation of the RSF model is depicted in [8].

In order to smooth the endocardial and epicardial contours, we use the following contour regularization term to penalize the arc lengths

$$\mathcal{L}(\phi) = \upsilon_1 \int |\nabla H(\phi(\mathrm{x}))|dx + \upsilon_2 \int |\nabla H(\phi(\mathrm{x}) - k)|d\mathrm{x} \quad (13)$$

where the arc lengths of the two level contours are calculated by these two terms in $\mathcal{L}(\phi)$.

Then our energy function can be written with energy terms (10)(12)(13) we defined above:

$$\mathcal{F}(\phi, f_1, f_2, f_3) = \mathrm{D}(\phi, \alpha) + \mathcal{E}(\phi, f_1, f_2, f_3) + \mathcal{L}(\phi). \quad (14)$$

For a fixed level set function ϕ, we minimized functional $\mathcal{F}(\phi, f_1, f_2, f_3)$ in (14) with respect to the functions $f_1(x), f_2(x)\ and\ f_3(x)$. By calculus of variations, it can be shown that the functions $f_1(x), f_2(x)\ and\ f_3(x)$ that minimize $\mathcal{F}(\phi, f_1, f_2, f_3)$ that satisfy the following Euler–Lagrange equations:

$$\int K_\sigma(x-y)\, M_i(\phi(y))(I(y) - f_i(x))dy = 0,\ i = 1,2,3 \quad (15)$$

From (15), we obtain

$$f_i(x) = \frac{K_\sigma(x) * [M_i(\phi(x))I(x)]}{K_\sigma(x) * M_i(\phi(x))}, i = 1,2,3 \quad (16)$$

which minimize the energy functional $\mathcal{F}(\phi, f_1, f_2, f_3)$ for a fixed ϕ. The functions $f_1(x), f_2(x)\ and\ f_3(x)$ given by (16) are weighted averages of the intensities in a neighborhood of x, whose size is proportional to the scale parameter σ.

Energy equation (14) can be minimized by gradient flow method:

$$\frac{\partial \phi(\mathrm{x})}{\partial t} = \lambda_1 e_1(\mathrm{x})\delta(\phi(\mathrm{x})) - \lambda_2 e_2(\delta(\phi(\mathrm{x})) - \delta(\phi(\mathrm{x}) - k)$$

$$-\lambda_3 e_3(\mathrm{x})\, \delta(\phi(\mathrm{x}) - k)$$

$$+(\upsilon_1 \delta(\phi(\mathrm{x})) + \upsilon_2 \delta(\phi(\mathrm{x}) - k) div(\tfrac{\nabla \phi(\mathrm{x})}{|\phi(\mathrm{x})|})$$

$$+\mu(\nabla^2 \phi(\mathrm{x}) - \alpha(\mathrm{x}) div(\tfrac{\nabla \phi(\mathrm{x})}{|\phi(\mathrm{x})|}) \quad (17)$$

where

$$e_i(\mathrm{x}) = \int K_\rho(\mathrm{y}-\mathrm{x})|I(\mathrm{x}) - f_i(\mathrm{y})|^2 dy,\ \ i = 1,2,3\,.$$

We use this model to segment LV and RV from MR cardiac images with an initialization of applying DRLSE method. The specific process and experiments are described in next section.

III. EXPERIMENTAL RESULTS

A. *Preliminary Segmentation of Left and Right Ventricles Using DRLSE*

In this first step of our method, we use DRLSE to perform a preliminary segmentation of left and right ventricles. In the first step, we placed two rectangles in the LV and RV for the initialization of DRLSE. Then the final zero level contour in DRLSE, as shown in Fig. 1 (b), were used in the initialization of the level set function in the subsequent distance regularized two-layer level set method.

Given the segmented left and right ventricles obtained in the first step, denoted by V_{left} and V_{right}, we constructed the initial level set function for the second step as:

$$\phi_0(\mathrm{x}) = \begin{cases} c, & x \in V_{left} \cup V_{right} \\ -c, & else \end{cases}$$

where c is a positive contant.

B. *Final segmentation results*

The results of LV and RV segmentation using two-layer distance regularized level set method after applying DRLSE initialization are shown in this part.

In this experiment, we set parameters as $\rho = 3, \mu = 1, \omega = 0.5, \lambda_1 = 0.03, \lambda_2 = 0.06, \lambda_3 = 0.024,$ and $\nu_1 = \nu_2 = 0.001 * 255 * 255$ in this model. Our approach has been tested on the datasets of MICCAI 2009 challenge on left ventricle segmentation and the datasets of MICCAI 2012 Right Ventricle Segmentation Challenge [16], which is available from the following link: http://www.litislab.eu/rvsc

LV and RV segmentation results of cardiac cine MR short-axis images are shown in Fig. 3. In Fig.3, four different patients' cardiac MR images are displayed in different columns. Row 1 and Row 2 are the original images and ground truth, respectively. Row 3 shows the results of our first step with DRLSE method used as initialization of second step. Row 4 is the final results of our distance regularized two-layer level set method. We use results in Row 3 as initialization of endocardial contour and choose k-level=30 as epicardial contour for our experiments, and then obtain final endocardial and epicardial contours. From experimental results, we can see that the two contours obtained after 900 iterations by our proposed algorithm can fit endocardium and epicardium of cardiac ventricles well.

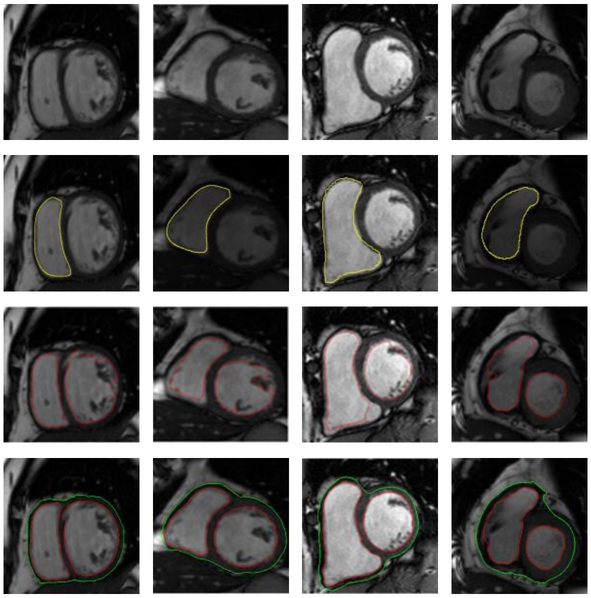


Figure 3: Results of our proposed method. *Row 1: original images, Row 2: ground truth, Row 4: results of DRLSE, Row 5: segmentation results of our proposed method.*

IV. DISCUSSION

A distance regularized two-layer level set model using DRLSE initialization is proposed in this paper to segment LV and RV from cardiac MR short-axis images. We apply DRLSE method as initialization of endocardial contour in the first step. Then we use DR2LS to obtain both endocardial and epicardial contours. The distance between the two level contours which represent endocardium and epicardium can be kept smoothly varing due to our distance regularization term. Our approach has been tested successfully on datasets of both MICCAI 2009 challenge on left ventricular segmentation and MICCAI 2012 Right Ventricle Segmentation Challenge. From experimental results, we can see that our approach has advantage over segmentation precision, and can retain the anatomical feature of the endocardium and epicardium. Algorithm proposed in this paper proves extremely effective in terms of segmenting LV and RV from cardiac MR images.

V. CONCLUSION

We have proposed a novel method for segmentation of cardiac left and right ventricles based on distance regularized level set evolution in (DRLSE) [7] and its extension to the distance regularized two-layer level set (DR2LS) model in [17]. Our method draws upon the anatomical geometry of the heart in the proposed level set formulation, which contributes to overcome the difficulty caused by low contrast between myocardium and adjacent tissues. Our method has been tested on cine MR images with promising results.

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