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Markovian Level Set for Echocardiographic Image Segmentation

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Abstract—Owing to the large amount of speckle noise and ill-defined edges present in echocardiographic images, computer-based boundary detection of the left ventricle (LV) has proved to be a challenging problem. In this paper, a Markovian level set method for boundary detection in long-axis echocardiographic images is proposed. It combines MRF model which makes use of local statistics with level set method which handles topological changes, to detect a continuous and smooth LV boundary. Experimental results show that high accuracy is achieved with the proposed method. The experimental results are also compared with two related MRF-based methods to demonstrate its superiority.

I. INTRODUCTION

Two-dimensional (2-D) echocardiography is a valuable diagnostic imaging modality for patients with heart disease. The quantification of the cardiac function depends on accurate tracing of the LV boundaries in the echocardiographic images. Manual tracing by expert clinicians is tedious and significant intraobserver and interobserver variability may be present. With the increased computational power, automatic detection of the LV and particularly the endocardial boundary from echocardiographic images becomes a very useful step in the clinical diagnosis. However, the inherent characteristics of B-scan ultrasound images, including low contrast, speckle noise, dropouts, and ill-defined edges greatly complicate automatic LV boundary detection and volume visualization.

Markov Random Field (MRF) and Bayesian based methods have been investigated by several researchers to segment ultrasound images [1]–[3]. A MRF is a probabilistic model of the elements of a multidimensional random variable where the components have only local interactions [4]. According to MRF theory, an energy function of the field can be derived from neighbors and cliques. The Gibbs Sampler algorithm proposed by Geman and Geman [5] gives a constructive iterative procedure to realize the field in practical applications. Additionally, the Simulated Annealing (SA) algorithm [5] was proposed to find the maximum a posteriori (MAP) estimation of the field.

Osher and Sethian [6] introduced Level Set method for implementing curve propagation and accounting for automatic topology adaption. Several attempts are made to apply level set method on echocardiographic image segmentation [7]–[9].

In this paper, an algorithm named *Markovian level set* is proposed for boundary detection of the LV from long-axis echocardiographic images. The proposed method differs from

other MRF-based methods in that it combines the MRF and the level set method to alleviate some of the aforementioned problems.

II. METHOD

A. 2D polar coordinate system

In [10], a novel method for automatic ROI segmentation and LV center detection is presented. For boundary detection in long-axis echocardiographic images, the method is used as a preprocessing step to acquire the locations of ROI and LV center. The 2D polar coordinate system adopted is schematized in Fig. 1. As shown in Fig. 1, a circular region from the center is excluded from the ROI (gray zone). Let $\mathbf{r} = \{r^1, r^2, \dots, r^M\}$ represent the radial lines radiated from the center, where M is the total number of radial lines. On each radial line r^i , there are N_i neighboring radial positions within the ROI. A site in this system is denoted by s_j^i , where $i \in \{1, 2, \dots, M\}$ and $j \in \{1, 2, \dots, N_i\}$. Since the radial lines are distributed radially, not all the pixels within the ROI are included as a site.

The LV cavity is more like an ellipse than a circle in long-axis echocardiographic images. If the angle between each radial line is set to be the constant value $(2\pi/M)$ [2], the resulting control points of LV contour will be very uneven: dense at the end of x -axis and loose at the end of y -axis. Nonuniform distributed radii have to be used [11] to overcome this problem. Considering the equation of ellipse, the angle of the i th radial line is then given by

$$\theta_i = \arg \tan \left(\frac{b}{a} \tan \left(\frac{2\pi(i-1)}{M} \right) \right), \quad (1)$$

where a and b are the minor and major radii of the ellipse respectively. Considering the LV cavity, the ratio of long-axis to short-axis is approximately 3/2, thus b is set to be 3/2 of a .

B. MRF Model

On a finite grid S (the gray zone in Fig. (1)), the sites $s \in S$ correspond to each component of the random variable. Consider a couple of random fields $Z = (X, Y)$, where $Y = \{Y_s, s \in S\}$ is the field of observations and $X = \{X_s, s \in S\}$ is the label field. A MRF is defined in terms of a neighborhood. Given a neighborhood, a clique is a subset of this neighborhood where all the components are neighbors of one another. Similar to 2D MRF model in Cartesian

Fig. 1. The 2D polar coordinate system.

Fig. 2. The second-order neighborhood system in (a) Cartesian coordinates and (b) polar coordinates; (c) all doubleton (double-pixel) cliques.

coordinates, the second-order neighborhood system is used for each site s_j^i :

$$\mathcal{N}(s) = \{s_{j+1}^i, s_{j-1}^i, s_j^{i+1}, s_j^{i-1}, s_{j+1}^{i+1}, s_{j-1}^{i+1}, s_{j+1}^{i-1}, s_{j-1}^{i-1}\}. \quad (2)$$

It is noted that the neighborhood of the radial system is fan-shaped and that of the Cartesian system is a square (Fig. (2)).

From neighbors and cliques, energy functions of the field are defined. For the m th class in the k th feature component, the distributions of all feature data are assumed to be Gaussian with different means μ_m^k and standard deviations σ_m^k . The feature energy resulting from data-likelihood function is given by:

$$E_F(y_s|x_s) = -\log p(y_s|x_s) = \sum_{k=1}^K \left[\frac{(y_s^k - \mu_m^k)^2}{2\sigma_m^k{}^2} + \log(\sqrt{2\pi}\sigma_m^k) \right]. \quad (3)$$

and the region energy resulting from a *prior* distribution

function is given by:

$$E_R(x_s) = -\log p(x_s) = \beta \sum_{s_n \in \mathcal{N}(s)} \delta(x_s, x_{s_n}). \quad (4)$$

where β is the Gibbsian parameter and $\delta(x_s, x_{s_n})$ is -1 when $x_s = x_{s_n}$ and 1 otherwise.

In the original MRF model, the segmentation is performed by maximizing the *a posteriori* segmentation probability, i.e. minimizing the energy function ($E=E_F+E_R$) of given the input image. In the proposed Markovian level set model, it is performed by updating the level set function:

$$\phi_t = E(x_1|y) - E(x_2|y). \quad (5)$$

Given an initial label field $X = \{X_s, s \in S\}$, $X \in \{e_0 = \text{blood}, e_1 = \text{myocardium}\}$, its edge set C is regarded as a zero level set and the initial level set function is set as follows

$$\phi(s, t=0) = \begin{cases} d, & \text{if } x_s = e_1 \\ -d, & \text{if } x_s = e_0. \end{cases} \quad (6)$$

where d is the distance from x_s to C .

The zero level set of the evolving function $\phi(s, t) = 0$ always matches the propagating front. Along each radial line, the desired LV endocardial boundary corresponds to the *first positive zero-crossing*.

C. Deformation Smoothness

The deformation smoothness is regulated in terms of first and second derivatives in the snake models. In the Markovian snake model, the derivatives are carried out in polar coordinates instead of Cartesian coordinates to avoid the trend of snake to vanish to a point if there is no image force. Traditionally the derivatives are approximated by finite differences of the contour vectors. In the case of level set method where the propagating curve is implicitly represented by the zero level set function, the curvature $\mathcal{K}$ can be estimated directly from the level set function $\phi(x, y)$:

$$\mathcal{K} = \frac{\phi_{xx}\phi_y^2 - 2\phi_{xy}\phi_x\phi_y + \phi_{yy}\phi_x^2}{(\phi_x^2 + \phi_y^2)^{3/2}}. \quad (7)$$

The above equation is used for square neighborhood system in Cartesian coordinates and is not applicable for fan-shape neighborhood system in polar coordinates.

A *boundary point* $b^i(x, y)$ is defined as the first positive zero-crossing of the level set function, along each radial line r^i . The curvature is derived by

$$\mathcal{K} = \frac{\dot{x}\ddot{y} - \dot{y}\ddot{x}}{(\dot{x}^2 + \dot{y}^2)^{3/2}}, \quad (8)$$

where the first $(\dot{x}, \dot{y})$ and second $(\ddot{x}, \ddot{y})$ derivatives are calculated from the coordinates of b^i and its neighbors b^{i-1} and b^{i+1} . For non-boundary points, the curvature at this site is set to zero.

In Eqn. (8), the (x, y) coordinates have to be translated with the LV center as the origin ($x = 0, y = 0$). The boundary smoothness is more readily and explicitly achieved in the polar coordinate system. The norm of the gradient ($|\nabla\phi|$)

is not considered since the *tangential* smoothness is directly regulated by $\mathcal{K}$. The updating of the level set function becomes

$$\phi_t = E(x_1|y) - E(x_2|y) + c\mathcal{K}. \quad (9)$$

where c is the weight of smoothness.

D. Segmentation Procedure

- Starting from the original (highest resolution) input image, a multiscale pyramid is built using the discrete wavelet transform [12]. From the image in each scale and the corresponding ROI and LV center, a 2D polar system is built. The intensity and location of each site on each radial line is recorded. During the segmentation procedure, these sites are classified as pixels of blood or myocardium.
- An initial classification is carried out at the coarsest scale using K-means clustering algorithm. It is observed that the myocardium appears to be brighter pixels than the blood. From the resulting two classes of pixels, the one with higher average intensity is labeled as $\{e_1 = \text{myocardium}\}$ and the one with lower average intensity is labeled as $\{e_0 = \text{blood}\}$.
- Starting from the initial classification, the algorithm alternates between the updating of level set function and the estimation of model parameters, until there is no further change in the label. Given the region labels $x \in \{e_0, e_1\}$ within a window centered at s , the local class means μ_m and variances σ_m for both classes ($m = 0, 1$) are estimated.
- Initially, for robust estimation of the model parameters, a large window size W is used for the coarsest scale. As the algorithm progresses to finer scales, smaller windows are used to give more reliable and accurate estimations of the local characteristics.
- Before and after updating the level set function, there are iterative conversions between the label field X and the level set function ϕ . A level set function can be derived from a label field X using Eqn. (6). On the other hand, a label field can be derived from a level set function using

$$x_s = \begin{cases} e_1, & \text{if } \phi(s, t) > 0 \\ e_0, & \text{if } \phi(s, t) < 0. \end{cases} \quad (10)$$

III. RESULTS

The proposed automated method is applied to five sequences of long axis echocardiographic images. Five parameters are involved in the proposed method: the Gibbsian parameter $\beta = 0.1$ ($\Delta\beta = 0.04$), the number of radii $M = 60$, the weight for tangential smoothness $c = 1$, the window size W set to 1/4 of the whole image size, and the number of resolution levels $L = 4$. The same set of parameters are used in all the experiments.

The results of boundary detection by simple 2D MRF in polar coordinates (P-MRF) and 2D MRF in Cartesian coordinates (C-MRF) are presented to validate the effectiveness of the proposed Markovian level set (MLS) method. The label fields and the resulting boundary points obtained using the

three methods are displayed in Fig. 3 for comparison. In this figure, the results are obtained without control of deformation smoothness, i.e. $c=0$, to give a fairer comparison. It can be observed that MLS generates less false boundary points than P-MRF (Fig. 3(d)), and does not miss true boundary points like C-MRF (Fig. 3(e)) at regions of low contrast.

To assess the accuracy of the methods, the boundaries are compared with those drawn by experienced clinicians. Two boundary error metrics are used : Hausdorff distance and the mean absolute distance [13]. Another standard measure used is the Jaccard similarity coefficient (Intersection/Union) [14], which compares the areas enclosed by the boundary detected by the computer-aided methods and the boundary drawn by the expert. The value ranges from 0 (no overlap) to 1 (total overlap) and the higher value means better correlation. The average normalized boundary errors and area correlation for all the 86 images are listed in Table I. On the average, the proposed MLS method is better than P-MRF and C-MRF methods.

IV. CONCLUSION

A novel method combining MRF and level set is proposed to automatically detect the boundary of the left ventricle from echocardiographic images. A 2D MRF in polar coordinates is used, where the local smoothness and the image data are imposed by a Bayesian framework. By iterative conversion between the label field and the level set function, the segmentation process is carried out by updating the level set function. The proposed method is tested using five image sequences from different patients and modalities. Experimental results show that the computer-detected boundaries are highly correlated with expert-drawn boundaries and outperform the P-MRF and C-MRF methods.

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Fig. 3. Intermediate results obtained from the three method: (a), (d) P-MRF, (b), (e) C-MRF, and (c), (f) MLS using the same image. (a)-(c): segmented myocardium-labeled fields. (d)-(f): boundary points detected from the label fields.

TABLE I
AVERAGE NORMALIZED BOUNDARY ERRORS AND AREA CORRELATION.

Error Measures	P-MRF	C-MRF	MLS
Norm. HE	7.50 ± 2.50 %	6.85 ± 2.25 %	6.19 ± 2.37 %
Norm. ME	1.90 ± 0.45 %	2.15 ± 0.67 %	1.88 ± 0.43 %
Intersection/Union	0.800 ± 0.098	0.727 ± 0.137	0.797 ± 0.051

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