MARKOVIAN LEVEL SET: A NEW METHOD FOR BOUNDARY DETECTION FROM ECHOCARDIOGRAPHIC IMAGES

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ABSTRACT

Computer-based boundary detection in Echocardiographic Images is a challenging problem, due to the large amount of noise and the poor contrast presented. In this paper, a Markovian level set method is proposed for boundary detection in long-axis echocardiographic images. It combines MRF model which makes use of local statistics with level set method which handles topological changes, to ensure that the resulting boundary is continuous and smooth. Experimental results show that high accuracy is achieved with the proposed method.

1. INTRODUCTION

Two-dimensional (2-D) echocardiography is a valuable diagnostic imaging modality for patients with heart disease. With the increased computational power, automatic detection of the left ventricle (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.

Many sophisticated techniques have been proposed for boundary detection from echocardiographic images. Markov Random Field (MRF) and Bayesian based methods have been investigated by several researchers to segment ultrasound images [1–3]. Several attempts are made to apply the level set method on echocardiographic image segmentation [4–6].

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

2. METHOD

2.1. 2D polar coordinate system

From the given image and the corresponding ROI and LV center, a 2D polar system is built and schematized in Fig. 1. As shown in Fig. 1, a circular region from the center is excluded from the ROI (gray zone). Let $\mathbf{r} = \{r^1, r^2, ..., r^M\}$ represent the radial lines eradiated 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 $i \in \{1, 2, ..., M\}$ and $j \in \{1, 2, ..., N_i\}$. Since the radial lines are distributed radially, not all the pixels within the ROI are included as a site. We assume that the left ventricular boundary is a single-value function in polar coordinates whose origin is the center of the LV.

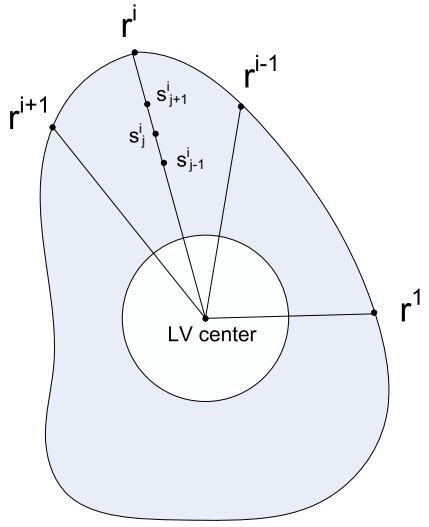

Fig. 1. The 2D polar coordinate system.

2.2. MRF Model

A MRF is a probabilistic model of the elements of a multidimensional random variable where the components have only local interactions [7]. 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

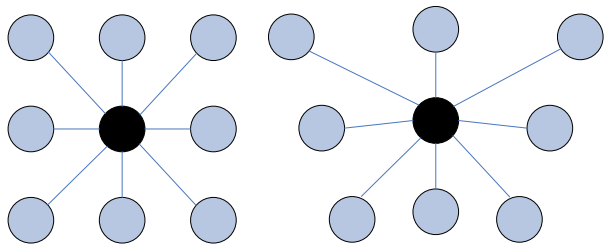

Fig. 2. The second-order neighborhood system in (a) Cartesian coordinates and (b) polar coordinates.

clique is a subset of this neighborhood where all the components are neighbors of one another. Similar to 2D MRF model in Cartesian coordinates, the second-order neighborhood system is used for each site s_j^i:

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

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

From neighbors and cliques, energy functions of the field are defined. According to the Central Limit Theorem, the average of a large number of random variables must tend toward a Gaussian distribution around their collective mean. For the mth class in the feature component, the distributions of all feature data are assumed to be Gaussian with different means μ^m and standard deviations σ^m. The feature energy resulting from data-likelihood function is given by:

$$E_F(y_s|x_s) = -\log p(y_s|x_s) = \frac{(y_s - \mu_s^m)^2}{2\sigma_s^{m2}} + \log(\sqrt{2\pi}\sigma_s^m). \tag{2}$$

and the region energy resulting from *a prior* distribution function is given by:

$$E_R(x_s) = -\log p(x_s) = \beta \sum_{s_n \in \mathcal{N}(s)} \delta(x_s, x_{s_n}). \tag{3}$$

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. Osher and Sethian [8] introduced Level Set method for implementing curve propagation and accounting for automatic topology adaption. By introducing the level set formulation, the curve $C(p,t)$ can be considered as the zero level set of a time-varying function $\phi(x,y,t) : [0,a] \times [0,b] \rightarrow \mathcal{R}$. $\phi(x,y,t)$ is defined as a distance function of point (x,y) to the zero level set with negative in the interior and positive at the exterior of the zero level set or vice versa. In the proposed Markovian level set model, it is performed by updating the level set function:

$$\phi_t = E(x_1|y) - E(x_2|y). \tag{4}$$

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

$$\phi(s, t=0) = \begin{cases} d, \text{ if } x_s = e_1 \\ -d, \text{ if } x_s = e_0. \end{cases} \tag{5}$$

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.

2.3. Deformation Smoothness

In some snake-based models, the derivatives are carried out in polar coordinates instead of Cartesian coordinates to avoid the trend of boundary to vanish to a point if there is no image force. Traditionally the derivatives are approximated by finite differences of the contour vectors.

For fan-shape neighborhood system in polar coordinates, the *curvature* is used to control the deformation smoothness. 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

$$\mathcal{K} = \frac{\dot{x}\ddot{y} - \dot{y}\ddot{x}}{(\dot{x}^2 + \dot{y}^2)^{3/2}}, \tag{6}$$

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. (6), 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

$$\phi_t = E(x_1|y) - E(x_2|y) + c\mathcal{K}. \tag{7}$$

where c is the weight of smoothness.

2.4. Segmentation Procedure

A hierarchical structure is adopted in the overall segmentation procedure as shown in Fig. 3.

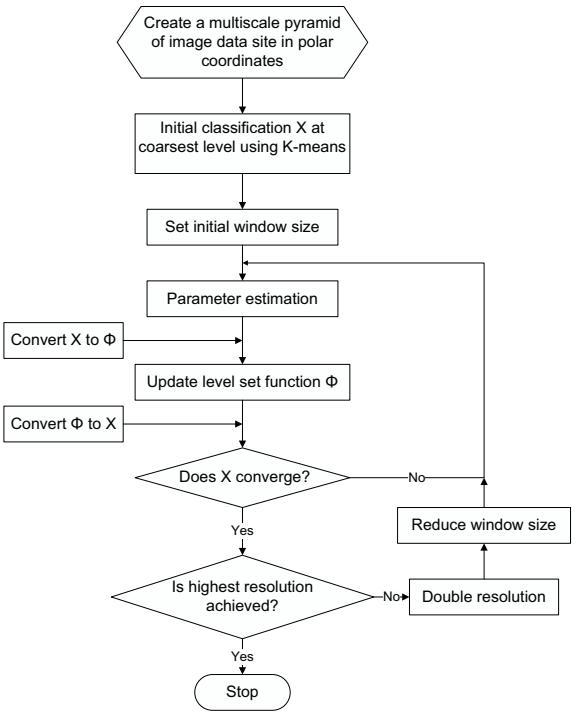

Fig. 3. The overall segmentation procedure.

3. RESULTS

Five parameters are involved in the proposed method: the Gibbsian parameter $\beta = 0.1$ (increased by $\Delta\beta = 0.04$ at each change of resolution level), 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 parameters are estimated in an ad hoc way. The same set of parameters are used in all the experiments.

The proposed automated method is applied to 86 long-axis echocardiographic images. The results of LV boundary detection from different sequences are given in Fig. 4.

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 mean absolute distance [9]. Another standard measure used is the Jaccard similarity coefficient (Intersection/Union) [10], which compares the areas enclosed by the boundary detected by the computer-aided methods and the boundary drawn by the expert. The average normalized Hausdorff distance, mean absolute distance and Jaccard similarity coefficient for all the 86 images are 6.19$\pm$2.37 %, 1.88$\pm$0.43 % and 0.797$\pm$0.051 respectively.

4. CONCLUSION

A novel method combining MRF and level set is proposed to automatically detect the boundary of LV from echocardiographic images. The local smoothness and the image data are imposed by a Bayesian framework, in a 2-D MRF in polar coordinates. By iterative conversion between the label field and the level set function, the segmentation process is carried out by updating the level set function. Experimental results show that the computer-detected boundaries are highly correlated with expert-drawn boundaries.

5. REFERENCES

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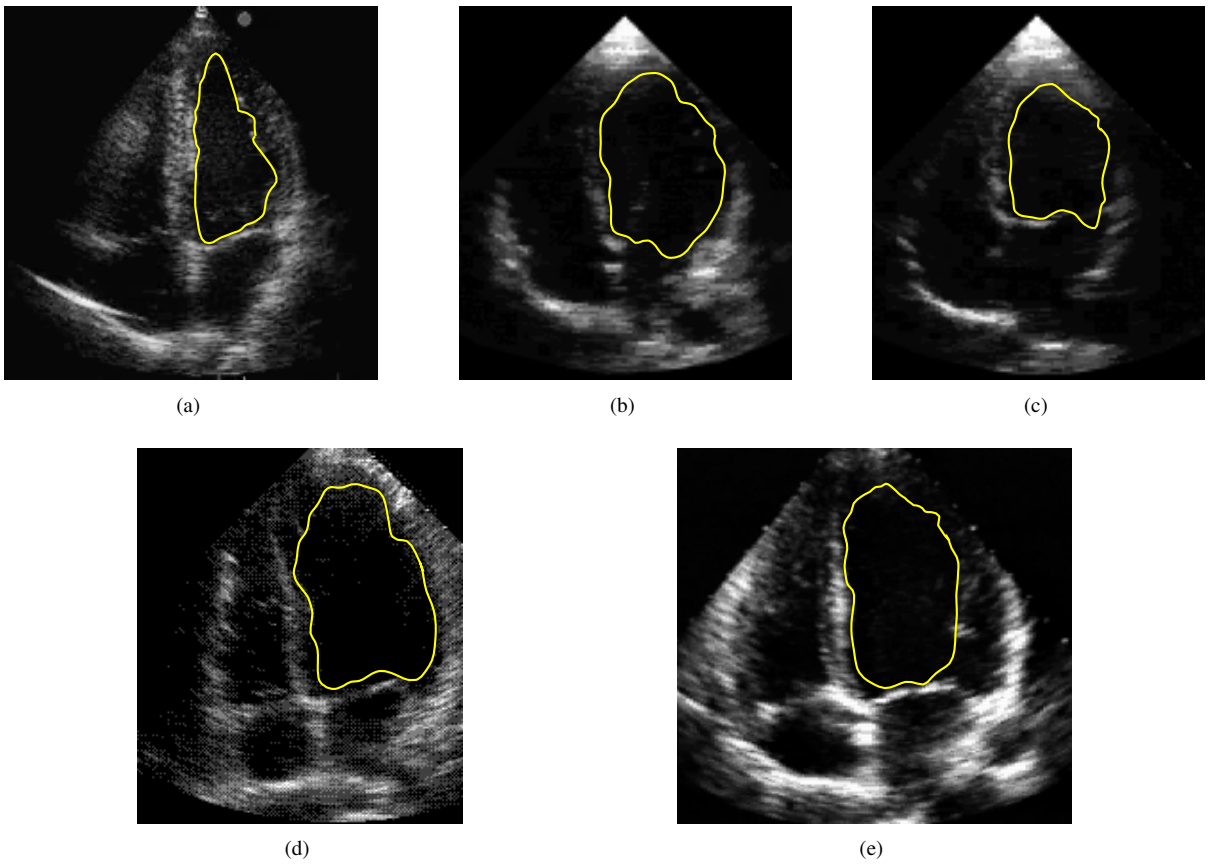

Fig. 4. Final LV boundaries obtained.

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