Segmentation of Myocardial Volumes from Real-Time 3D Echocardiography Using an Incompressibility Constraint^{*}

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Abstract. Real-time three-dimensional (RT3D) echocardiography is a new imaging modality that presents the unique opportunity to visualize the complex three-dimensional (3-D) shape and the motion of left ventricle (LV) *in vivo*. To take advantage of this opportunity, automatic segmentation of LV myocardium is essential. While there are a variety of efforts on the segmentation of LV endocardial (ENDO) boundaries, the segmentation of epicardial (EPI) boundaries is still problematic. In this paper, we present a new approach of coupled-surfaces propagation to address this problem. Our method is motivated by the idea that the volume of the myocardium is close to being constant during a cardiac cycle and takes this tight coupling as an important constraint. We employ two surfaces, each driven by the image-derived information that takes into account the ultrasound physics by modeling speckle using shifted Rayleigh distribution while maintaining the coupling. By evolving two surfaces simultaneously, the final representation of myocardium is thus achieved. Results from 328 sets of RT3D echocardiographic data are evaluated against the outlines of three observers. We show that the results from automatic segmentation are comparable to those from manual segmentation.

1 Introduction

RT3D echocardiography, an emerging trend in ultrasound imaging, provides truly volumetric images to allow the assessment of cardiac anatomy and function. For quantitative analysis of these volumetric data, it is desirable to automatically outline the shape of LV throughout a cardiac cycle. While there have been a number of publications describing ultrasound image segmentation techniques (see [1] for an overview), most of the attention has been given to ENDO boundary segmentation. Limited work has been done to detect EPI contours that are equally important in the quantitative assessment of myocardial deformation, especially when a biomechanical model is applied.

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The detection of EPI contours is more challenging than the detection of ENDO contours because the tissue/background contrast is lower than the blood pool/tissue contrast, resulting in the more ambiguous EPI boundaries, as shown in Figure 1. In addition, the speckle caused by the interference of energy from randomly distributed small scatters partially masks EPI boundaries. Furthermore, the EPI boundary is often occluded by other structures in the body such as the liver and the chest wall, that can have similar intensity to the myocardium. All these factors, when combined together, make EPI border detection an open problem.

There were some limited attempts to segment EPI boundaries [2][3][4]. These efforts, however, do not explicitly use the constraints due to myocardial structure. Our group previously developed a region-based approach to segment ENDO contours from rotational 3-D echocardiography [5]. In [6], we used coupled level sets to segment brain images. In this work, we extend our previous work to find EPI boundaries in RT3D echocardiography. Our method described in this paper is motivated by the nearly constant volume of the myocardium during the entire cardiac cycle and takes this property as an important constraint. By evolving ENDO- and EPI surfaces simultaneously, each driven by its own image derived region force while maintaining the coupling, a final representation of the ENDO- and EPI surface is thus achieved.

Fig. 1. The EPI contour is ambiguous while ENDO contour is clear. **Fig. 2.** Maximal likelihood fits of three models to RT3D echocardiographic data. Red: Rayleigh, Blue: Shifted Rayleigh, Black: Gamma.

2 Method

2.1 Statistical Modeling of Ultrasound Speckle

A number of statistical models, either theoretical or empirical, have been proposed. The Rayleigh distribution is the most popular model for fully developed speckle. Rician distribution, K-distribution, generalized K-distribution, homodyned K-distribution, and Rician Inverse of Gaussian distribution have also been considered. However, the analytical complexity of these complicated models is significant, particularly, when parameter estimation is required. Meanwhile,

largest significant value, and is thus chosen to model the speckle in RT3D echocardiographic images in our work.

2.2 Data Adherence Derivation

The strength of the signal due to the myocardial boundaries depends on the relative orientation of the border to transducer direction, and attenuation. Thus conventional intensity gradient-based methods have limited success in echocardiographic segmentation. A region-based deformable models, however, has shown promising performance in segmentation images with weak edges [9]. Let Ω be a bounded open subset of $\mathbb{R}^3$, and be partitioned by ENDO surface C^+ and EPI surface C^- into three regions - LV blood pool, LV myocardium, and background, which are denoted as Ω_1 , Ω_2 , and Ω_3 respectively. A region-based deformable model which maximizes the intensity homogeneity within each region can be defined as

$$L(C^+, C^-) = \log \mathcal{P}(I|C^+, C^-) = \sum_{l=1}^3 \int_{\Omega_l} \log \mathcal{P}(I; \min_l, \alpha_l) d\mathbf{x} \quad (1)$$

where $\mathcal{P}(I; \min_l, \alpha_l)$ is the shifted Rayleigh distribution. For $l = 1$, it models the distribution of speckle in LV blood pool. For $l = 2$, it models the distribution of speckle in LV myocardium.

While the histograms of speckle in blood pool and myocardium are unimodal, the background has a bimodal histogram, as shown in Figure 4. It is so because the background includes more than one tissue type (e.g. RV blood pool, RV myocardium, and other tissues)(as shown in Figure 3), and therefore modeling it with a single distribution would be insufficient. To tackle this problem, we use a mixture model and invoke EM algorithm to fit the background histogram. In Figure 4, we show the histogram of each region with the fitted shifted Rayleigh distribution function.

Fig. 4. The histograms of LV blood pool, LV myocardium, and background from RT3D echocardiographic data with estimated shifted Rayleigh distribution superimposed on them

2.3 Incompressibility Constraint

The myocardium is composed of cardiac muscle with specialized muscle fibers that act as a syncytium which contracts and relaxes spontaneously. Studies have

shown that the volume of myocardium varies less than 5% during a cardiac cycle [10][11]. Papademetris has previously applied a biomechanical model with a Poisson ratio close to 0.5 to recover the motion of myocardium during a cardiac cycle [12]. In this work, we use this incompressibility constraint as an important constraint to help detect the EPI border. Since myocardium is only nearly incompressible, it is more reasonable to formulate this constraint in a probabilistic framework, rather than impose a deterministic constraint.

We assume that the volume of myocardium from a cardiac sequence has a Gaussian distribution $\mathcal{N}(V_0, \sigma_0^2)$

$$\mathcal{P}(C^+, C^-) = \frac{1}{\sqrt{2\pi}\sigma_0} \exp \left\{ -\frac{(V - V_0)^2}{2\sigma_0^2} \right\} \quad (2)$$

where $V = \int_{\Omega_2} d\mathbf{x}$ is the volume of myocardium. Assuming that $0.025V_0$ is the maximum deviation extent (use $3\sigma_0$), we have the following relationship

$$3\sigma_0 = 0.025V_0 \quad (3)$$

$$\sigma_0 = \frac{1}{120}V_0 \quad (4)$$

2.4 Maximum a Posteriori Framework

To incorporate the data-derived information (section 2.2) and the incompressibility constraint (section 2.3) into a uniform framework, we formulate our problem in a Maximum A Posteriori (MAP) framework, which maximizes the posterior probability with the prior information of evolving surfaces.

$$\begin{aligned} (\hat{C}^+, \hat{C}^-) &= \arg \max_{C^+, C^-} \mathcal{P}(C^+, C^- | I) = \arg \max_{C^+, C^-} \underbrace{\mathcal{P}(I | C^+, C^-)}_{\text{adherence to data}} \underbrace{\mathcal{P}(C^+, C^-)}_{\text{incompressibility constraint}} \\ &= \arg \max_{C^+, C^-} \left\{ \sum_{l=1}^3 \int_{\Omega_l} \log \mathcal{P}(I; \min_l, \alpha_l) d\mathbf{x} - \frac{(V - V_0)^2}{2\sigma_0^2} \right\} \end{aligned} \quad (5)$$

The maximization of equation 5 can then be identified by the coupled Euler-Lagrange equations

$$\frac{\partial C^+}{\partial t} = \left\{ \log \frac{\mathcal{P}(I; \min_1, \alpha_1)}{\mathcal{P}(I; \min_2, \alpha_2)} - \frac{V - V_0}{\sigma_0^2} \right\} \mathbf{n}^+ \quad (6)$$

$$\frac{\partial C^-}{\partial t} = \left\{ \log \frac{\mathcal{P}(I; \min_2, \alpha_2)}{\mathcal{P}(I; \min_3, \alpha_3)} + \frac{V - V_0}{\sigma_0^2} \right\} \mathbf{n}^- \quad (7)$$

where $\mathbf{n}^+$ and $\mathbf{n}^-$ are the normals of C^+ and C^- respectively.

3 Results

The RT3D echocardiographic data were acquired using a Philips SONOS 7500 machine. This system uses a 4-MHz matrix-array transducer which consists of

3000 miniaturized piezoelectric elements and offers steering in both azimuth and elevation of the beam, permitting real-time 3-D volumetric image acquisition and rendering.

We performed experiments on 22 sequences of RT3D echocardiographic data, and each sequence has 13-17 frames depending on the heart rate. Hence, we ran our algorithm with a total of 328 sets of volumetric data. Considering the intra- and inter- observer variability, we asked three experts, blind to each other, to independently outline the ENDO- and EPI contours of all the frames of image sequences. The average volume of myocardium in the first frame was taken to be the mean volume of myocardium in that sequence. Considering the temporal continuity of a cardiac sequence, our algorithm used the segmented contour of the current frame as an initial contour for the subsequent frame. It normally took 5-8 minutes to segment one frame with the size of $164 \times 164 \times 208$.

Fig. 5. Example of segmented ENDO and EPI contours from frames 2, 4, and 6 during cardiac systole

Fig. 6. Result without the incompressibility constraint

In Figure 5, we show the long axis view of segmented ENDO- and EPI contours at frames 2, 4, and 6 during cardiac systole. In Figure 6, we compare the results with and without the incompressibility constraint. It shows that, without incompressibility constraint, the EPI boundary leaked while the ENDO boundary was still located. Figure 7 shows an example of volumetric RT3D echocardiographic data with ENDO and EPI surfaces superimposed on it. Figure 8 shows a good correlation between the manually identified and automatic algorithm determined volume of myocardium when the incompressibility constraint was applied.

In addition, we computed two distance error metrics and two area error metrics, namely, mean absolute distance (MAD), Hausdorff distance (HD), the percentage of correctly segmented voxels (PTP), and the percentage of false positives (PFP). Let $A = \{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n\}$, $B = \{\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_m\}$, Ω_a be the region enclosed by C_a , and Ω_m be the region enclosed by C_m . We define $MAD = \frac{1}{2} \left\{ \frac{1}{n} \sum_{i=1}^n d(\mathbf{a}_i, B) + \frac{1}{m} \sum_{i=1}^m d(\mathbf{b}_i, A) \right\}$, $HD = \max \left(\max_i \{d(\mathbf{a}_i, B)\} + \max_j \{d(\mathbf{b}_j, A)\} \right)$, where $d(\mathbf{a}_i, B) = \min_j \|\mathbf{b}_j - \mathbf{a}_i\|$. We also define $PTP = \frac{\text{Volume}(\Omega_a \cap \Omega_m)}{\text{Volume}(\Omega_m)}$ and $PFP = \frac{\text{Volume}(\Omega_m) - \text{Volume}(\Omega_a \cap \Omega_m)}{\text{Volume}(\Omega_a)}$. While MAD represents the global disagreement between two contours, HD compares two contours locally.

Tables 2 and 3 compare the results from automatic segmentation to those from manual segmentation. Table 2 shows that ENDO boundaries were detected with

Fig. 7. Example of**Fig. 8.** Linear regression analysis of myocardial volume with and without the incompressibility constraint**Table 2.** Comparison automatic outline to three observers' outline of ENDO boundaries

	MAD(mm)	HD(mm)	PTP(%)	PFP(%)
Automatic-manual (with constraint)	1.45 ± 0.30	2.41 ± 0.47	96.21 ± 1.97	4.04 ± 1.90
Automatic-manual (without constraint)	1.50 ± 0.28	2.43 ± 0.59	95.71 ± 1.85	4.17 ± 1.80
Manual-Manual	1.30 ± 0.27	2.14 ± 0.52	96.34 ± 1.93	4.00 ± 1.84

Table 3. Comparison of automatic outline to three observers' outline of EPI boundaries

	MAD(mm)	HD(mm)	PTP(%)	PFP(%)
Automatic-manual (with constraint)	1.75 ± 0.50	2.90 ± 0.80	94.35 ± 1.02	5.46 ± 0.76
Automatic-manual (without constraint)	4.86 ± 1.86	6.87 ± 2.34	77.92 ± 6.97	21.14 ± 7.87
Manual-manual	2.56 ± 0.78	3.21 ± 0.96	94.89 ± 2.34	5.23 ± 0.80

sufficient accuracy even if the incompressibility constraint was not applied. This is because the ENDO boundaries are relatively clear compared to the EPI boundaries. However, Table 3 shows that for EPI boundaries, when the incompressibility constraint was not applied, computer-manual MAD was 3.1mm larger than manual-manual MAD and computer-manual PTP&PFP were 13% – 17% worse than manual-manual PTP&PFP. This is because the EPI boundaries leaked out without the constraint. When the incompressibility constraint was applied, however, the automatic algorithm produced results with comparable accuracy to a manual segmentation. Furthermore, we observed from Tables 2 and 3 that the variability of manual-manual segmentation was smaller for ENDO than for EPI. This is probably because EPI boundaries are more ambiguous for observers to detect, which was also the reason we have multiple observers instead of a single one.

4 Conclusion

In this paper, we presented a novel approach to segmenting the full myocardial volume from RT3D echocardiographic images using the incompressibility property that the volume of myocardium varies less than 5% during a cardiac cycle. Our experiments showed that computer-generated contours agreed with the observers' hand-outlined contours as much as the different observers agreed with each other. Future work includes the joint segmentation and motion analysis of echocardiographic sequences.

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