Robust Segmentation of Freehand Ultrasound Image Slices Using Gradient Vector Flow Fast Geometric Active Contours

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Abstract

We propose a new semi-automatic segmentation strategy on echocardiographic images, which combines a recently introduced Gradient Vector Flow (GVF) Fast Geometric Active Contour (GAC) model and a modified level sets methods applied to echocardiographic data by Corsi et al. [1]. We call it adaptive GVF GAC model. We note that echoardiographic images are characterized by high levels of speckle noise, weakly-defined boundaries and severe gaps. We show that the new method, adapted for single object segmentation, can provide significantly improved performance over a competing level set method, and that was in turn shown to perform better than the original Gradient Vector Flow method. The new method modifies the advection term in the speed function adaptively by estimating how close the propagated curve is to the target boundaries. We show both synthetic and real, freehand ultrasound image and echocariographic image examples to illustrate the robustness and accuracy of the new segmentation method.

1. Introduction

The use of 3D echocardiographic methods allows us to provide accurate measurements of 3D volumes that do not require assumptions on cardiac anatomy. Most 3D reconstruction methods are focused on single-view reconstructions of the left ventricle by a 2D probe or direct imaging by a real-time 3D probe [1]. We have recently introduced a multi-view, freehand ultrasound imaging system that can combine 3D reconstructions from multiple acoustic views, and provide accurate 3D reconstructions that are significantly better than reconstructions from a single 3D view [2, 3]. However, our multi-view reconstruction system relied on manual segmentation of the individual 2D image slices. Manual tracing of heart boundaries is tedious, time-consuming and subject to reader variability. In this paper, we investigate automatic segmentation methods for segmenting the individual image slices.

Echocardiographic image segmentation techniques face a number of challenges due to the characteristics of the images: poor image contrast, high-level speckle noise, weakly defined boundaries, and boundary gaps. Traditional segmentation methods are often unable to perform adequately on echocadiographic images. Recently, new deformable models have been extensively developed and used in this field. There are mainly two types of deformable models: parametric and geometric deformable models. In parametric deformable models, the evolved curve is explicitly represented in parametric form. The model must be reparametrized dynamically when dealing with topological changes, which require sophisticated schemes. Geometric deformable models have the advantage that they can automatically handle topological changes. The evolved curve is implicitly represented as level sets of a higher dimensional scalar function. The advantage of this approach is that the level set function remains a valid function while the evolved curve changes its topology.

Recently, Corsi et al. [1] developed a level set method to semi-automatically segment real-time 3D echocardiographic images, and then used the segmented images to reconstruct the left ventricle, and estimate its volume. In their study, the initial surface points had to be chosen close to the boundaries of the LV chamber. This was necessary since the expansion term had been removed from the deformable model to avoid edge-leaking at poor edges and edge gaps. In addition, we note that the original Gradient Vector

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Flow method [4] has been extended into three different models of geometric GVF active contours [5-7]. In this paper, we combine the fast geometric GVF active contour model developed by Paragios et al in [7] and Corsi's method [1] to implement automatic segmentation of echocardigraphic images. The useful property of this approach is that it allows for relatively simple and free initialization of the deformable model, while avoiding edge leaking at the poor edges and boundary gaps in echocardiographic images.

2. Method

Corsi *et. al*. [1] applied level set techniques to semi-automatically segment 3D echocardiographic data using:

$$\varphi_t = g\,\varepsilon\,K\,|\nabla\varphi| + \beta\nabla g\bullet\nabla\varphi \quad . \qquad (1)$$

In (1), $\varphi(\vec{x},t)$ is a higher-dimensional scalar function, called the level set function. It represents the moving front as the zero level set where $\varphi(\vec{x},t)=0$. We also have that K is the mean curvature, εK is the diffusion term that is used to smooth out the high curvature regions, while g is a monotonically decreasing function that satisfies: $g(0)=1, \quad \lim_{x\to\infty} g(x)\to 0$. In echocardiographic image segmentation, g is usually used as an edge indicator applied to a Gaussian smoothed image:

$$g(\vec{x}) = \left\{1+\left(\left|\nabla\left(G_\sigma * I(\vec{x})\right)\right| \big/ \alpha\right)^2\right\}^{-1} \qquad (2)$$

where $f(\vec{x}) = \left|\nabla\left(G_\sigma * I(\vec{x})\right)\right| \big/ \alpha$ is the edge map function. The vector field ∇g is an advection term that always points towards image boundaries. The parameters β,ε are used to control the strength of advection and limit the regularization. This approach worked well only when the initial curve was close enough to the actual endocardial boundaries. To overcome this weakness, we considered integrating gradient vector flow (GVF) in a geometric deformable model. GVF force has a large capture range and allows deformable models to be initialized far away from the object boundary [4]. Paragios used fast GVF geometric active contours that are robust to the initial conditions and allow active contours to undergo topological changes [7]:

$$\varphi_t = g\left[\varepsilon K|\nabla\varphi| - \left(\left[\hat{u},\hat{v}\right]\bullet\nabla\varphi\right)\right]. \qquad (3)$$

In (3), the vector field $\left[\hat{u},\hat{v}\right]$ is called gradient vector flow (GVF), a two-dimensional vector filed that diffuses the image gradient information toward the homogenous background. It is a bidirectional flow that propagates the curve toward the object boundary from either side. It has the advantage that it is not sensitive to the initial curve. In our experiments, we combined these two approaches; Corsi's method and Paragios' method together using a global indicator function δ. Initially, $\delta=0$, allowing the deformable model curve to get closer to the target boundary under GVF GAC deformable model. When the curve is sufficiently close, then we get $\delta=1$, advection term is then dominated by the vector field ∇g, to avoid edge leaking on the poor endocardial boundaries and boundary gaps. Actually the pixel value of the edge map gives the information of how close the pixel on evolved curve is approaching to the target boundary. To determine when to set $\delta=1$, we use a training set to estimate the average value of the edge map over real boundaries and a threshold is determined. Then, following the training phase, we simply set $\delta=1$ when the average value of the edge map over the all pixels on the zero level set of the evolved curve is above the threshold. The combined adaptive GVF GAC model equation is:

$$\varphi_t = g\varepsilon K|\nabla\varphi| - (1-\delta)\left\{\beta\left(\left[\hat{u},\hat{v}\right]\bullet\nabla\varphi\right)\right\} + \delta\beta\nabla g\bullet\nabla\varphi$$

3. Experimental Results

Both ultrasound phantom images and echocardiograpic images have been used for testing of the proposed segmentation method. We set the parameters as: $\varepsilon=0.8, \alpha=0.1, \beta=6$. Fig. 1 shows the comparison of the GVF geodesic active contour (GAC) model and the Corsi [1] level set technique on a simulated image and an ultrasound phantom image. The simulated image was formed by adding speckle noise as $J(\vec{x}) = I(\vec{x}) + n(\vec{x})\bullet I(\vec{x})$, to a grayscale image $I(\vec{x})$, where $n(\vec{x})$ is uniformly distributed random noise with zero mean and variance $\sigma^2=2$. Good results are obtained by first smoothing the image with a Guassian kernel ($\sigma=4$) before applying the GVF geodesic active contour method.

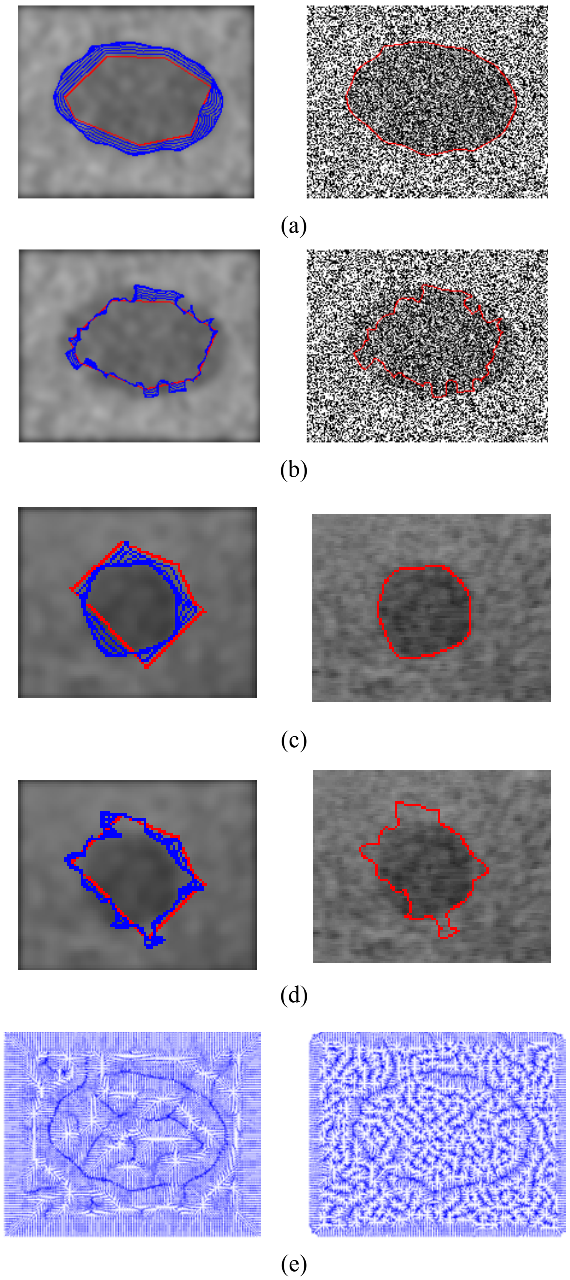

Fig. 1. (a) Curve evolution through time and final segmentation result by GVF GAC model; (b) Curve evolution through time and final segmentation result by Corsi's method; (c) and (d) Curve evolution and final segmentation result on a phantom image by GVF GAC and Corsi's method. (e) normalized GVF field and ∇g field.

We note that the strength of ∇g is too small to pull the propagating curve, especially when the expansion term is removed. We got a similar result even when we used the expansion term. Fig. 1(e) shows the normalized GVF field and ∇g field. The GVF field has much stronger attraction range than ∇g that is extended into the homogeneous region.

Fig. 2 shows satisfying segmentation results of two phantom ultrasound images for the small egg-shape object in a 3D calibration ultrasound calibration phantom, (Model 055, CIRS, USA). All of the images have high-level speckle noise, very low contrast and weak edges. Regardless of how we initialize the propagating curve, inside or outside or even across the object, the proposed GVF geometric active contours still converge to the actual boundary of the object (Fig. 1(c)).

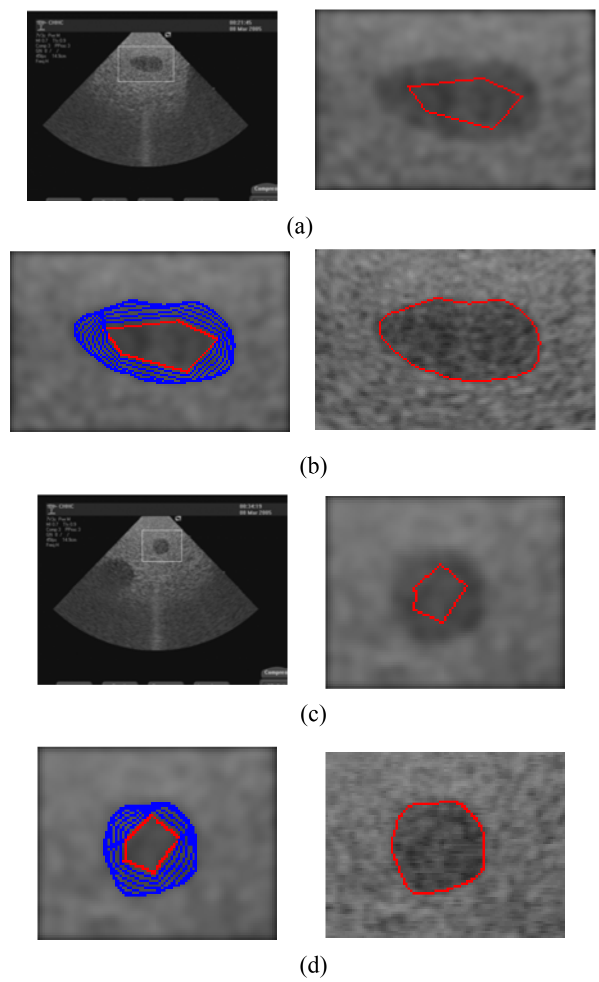

Fig. 2. Boundary extraction using GVF GAC model on ultrasound phantom images. (a) small egg long-axis image and initial curve, (b) curve evolution and final result. (c) small egg short-axis image and initial curve, (d) curve evolution and final result.

We note that the ultrasound phantom images can only be successfully segmented using the GVF geometric active contour (GAC) model, and that this approach is insensitive to how the segmentation is initialized. Yet, the same method failed on echocardiographic images because echoardiographic images have much more difficult boundaries, with some parts of the endocardial boundaries that are actually missing. GVF geometric active contours will leak from the weak edge region and boundary gaps. To overcome this problem, we use the proposed adaptive GVF GAC method that switches the advection term from the GVF vector field to the ∇g vector field. This approach yielded good results as shown in Figs 3 and 4.

Fig. 3 shows a parasternal short-axis view image slice segmentation. We set the parameters as before: $\varepsilon = 0.8, \alpha = 0.1, \beta = 6.$ The original cropped image was smoothed using a Gaussian kernal ($\sigma = 3$) before the deformable model was applied. Fig. 3(b) shows the curve evolution using the GVF GAC model. We note that the edge leaked from a small gap in the endocardial boundaries on the left side. Curve evolution by the proposed method is shown in Fig. 3(d), while the final segmentation result is shown in Fig. 3(e). In our experiments, the edge map average threshold was set to 40.

Fig. 4 shows automatic segmentation results for the apical long-axis view image slice from our 3D freehand ultrasound imaging system [2, 3]. We note that in Fig. 4(b), the GVF GAC method evolved the segmentation curve toward the field of view (fan-shape ultrasound field) boundary, because that boundary is much stronger than the endocardial boundaries. In Fig. 4(d), we can see that the proposed method did not suffer from this problem. This problem was alleviated by removing the GVF field and switching to the ∇g field. This approach resulted in the accurate segmentation of the endocardial boundaries.

4. Conclusion

The proposed adaptive GVF geometric active contour segmentation method, which combines two competitive approaches has proven to be more robust than the level set method due to Corsi et al [1]. The advantage of the proposed method is that it is insensitive to the initialization of the segmentation curve, while it avoids edge leaking at weak edges and boundary gaps in echoardiographic images. It allows for quick convergence and accurate segmentation. We are currently extending this work in 2D+T freehand ultrasound video image segmentation, multi-view reconstruction of the left ventricle, and LV volume quantification.

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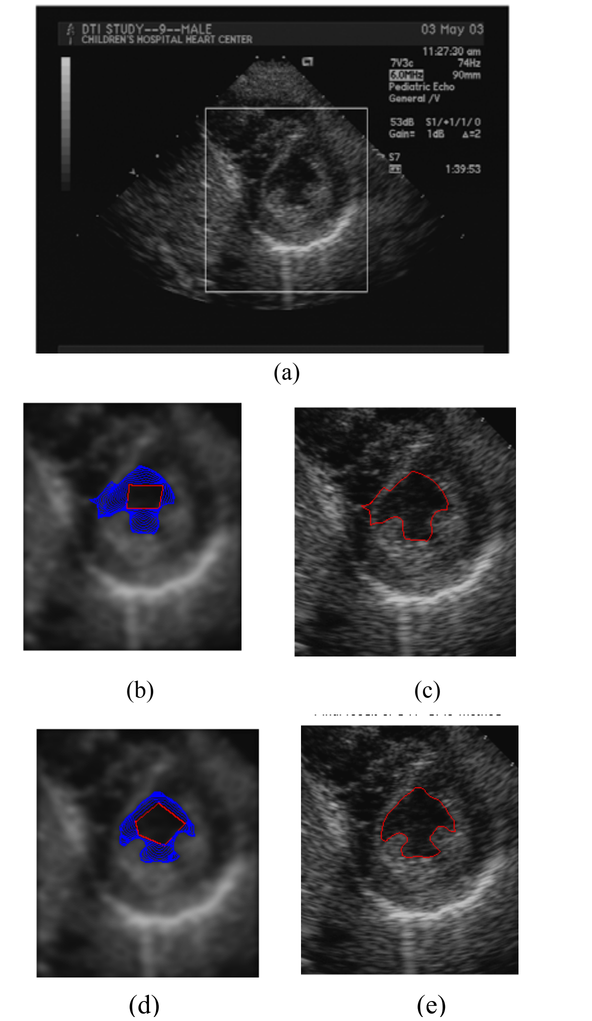

Fig. 3 Segmentation on parasternal short-axis view image. (a) original short-axis image, (b) curve evolution using GVF GAC model,(c) final result using GVF GAC model. (d) curve evolution using the proposed method. (e) final segmentation result using the proposed method.

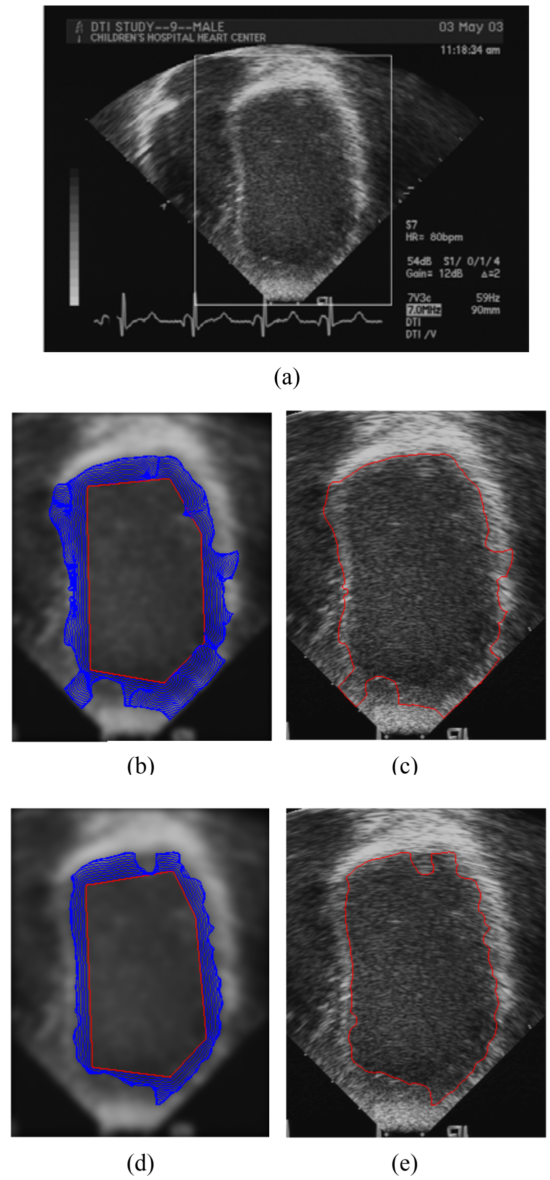

Fig. 4 Segmentation on apical long-axis view image. (a) original long-axis view image, (b) curve evolution using GVF GAC model,(c) final result by GVF GAC model. (d) curve evolution using the proposed method. (e) final segmentation result using the proposed method.