Robust Level Set for Heart Cavities Detection in Ultrasound Images

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Abstract

The class of geometric deformable models, also known as level sets, has brought tremendous impact on medical imagery due to its capability of topology preservation and fast shape recovery. Ultrasonic heart images are often characterized by high level of speckle noise causing erroneous detection of cavities. We propose a new stopping term for computing level sets in order to robustly detect the heart cavities in echocardiographic images. Robustness is ensured by the use of the coefficient of variation. Experimental results show significant improvement, especially for images acquired with low frequencies.

1. Introduction

The original level set method has been introduced by Osher and Sethian in [1]. Since its introduction, this technique has been used to solve various problems, such as image enhancement and noise removal [2, 3, 4], and contours detection [5, 6].

Speckle is a multiplicative locally correlated noise. The speckle reducing filters have originated mainly in the synthethic aperture radar community. The most widely used filters in this category, such as the filters of Lee [7], Frost [8] , Kuan [9], and Gamma Map [10], are based on the coefficient of variation. For ultrasound images, in order to develop a more efficient edge detector, the use of anisotropic diffusion and instantaneous coefficient of variation (ICOV) is proposed in [11, 12].

Our work proposes a level set method based on an original stopping term. The proposed method is adapted to speckle and allows robust detection of heart cavities. The new stopping term is founded on the Tukey norm [11].

The structure of this paper is as follows. Section 2 introduces the main concepts of level set methods. Section 3 shows a speckle caracterization with the coefficient of variation. Section 4 presents a new stopping term for the enhanced the level set algorithm. Section 5 compares the original and the new stopping term by using a synthetic image and a real ultrasound image. Finally, section 6 provides some conclusions.

2. Shape modeling using level set

Shape modeling using a level set approach considers a closed curve $\delta(t)$ moving in the plane, where $\delta(0)$ is the initial curve. The main idea is to embed this propagating curve as the zero level set of a higher dimensional function $\Phi(\delta, t)$ [5]. The equation representing the motion of the surface $\Phi(\delta, t)$ in the normal direction of the propagating curve is:

$$\frac{\partial \Phi}{\partial t} + F|\nabla \Phi| = 0 \tag{1}$$

where F is the propagation speed function. For certain forms of F, equation (1) reduces to a standard Hamilton-Jacobi equation. The speed function is defined by two terms:

$$F = F_A + F_G \tag{2}$$

where F_A represents a constant advection term that will force the curve to expand or contract uniformly based on its sign. The second term F_G depends on the geometry of the curve and acts to smooth out high curvature regions. For details on F_A and F_G see [5].

In order to stop the evolution of the curve at the edges, a function of the image gradient is classically used. This stopping term g is defined as follows:

$$g(\nabla I) = \frac{1}{1 + |\nabla(G * I)|^p}, p \geq 1 \tag{3}$$

The term $G * I$ in (3) is the convolution of the intensity image I with a gaussian filter G. The function g has values that are close to zero in regions where the gradient of the image is high, and values that are closer to one in the homogeneous regions. Taking into account the edge stopping function, the final equation is:

$$\frac{\partial \Phi}{\partial t} + gF|\nabla \Phi| = 0 \tag{4}$$

An important problem of the standard algorithm to solve (4) is its high complexity. In order to reduce the computation cost, other efficient methods have been proposed, such as the fast marching approach [13] and the narrow-band approach [14]. Our method is based on the latter approach.

3. The coefficient of variation as an edge detector for images affected by speckle

The techniques used to reduce the multiplicative noise in radar images use the coefficient of variation (CV) to characterize the noise. The CV, noted ξ can be estimated as:

$$\xi^2 = \frac{var(I)}{\overline{I}^2} \tag{5}$$

where $var(I)$ is the variance of the intensity image and $\overline{I}$ is the mean.

The local version γ of the CV calculated in the vicinity of a pixel s is:

$$\gamma^2(s) = \frac{1}{|\eta_s|} \sum_{p \in \eta_s} \frac{(I_p - \overline{I_s})^2}{\overline{I_s}^2} \tag{6}$$

η_s is a neighbourhood of s, $\overline{I_s}$ is the mean intensity of η_s, and I_p is part of η_s.

An image affected by multiplicative noise can be expressed as $I_{i,j} = R_{i,j} * n_{i,j}$ where R is the reflectivity and n a multiplicative noise. On an area Ω with N elements and constant reflectivity k, the previous equation can be written as:

$$I_{i,j} = k * n_{i,j} \tag{7}$$

Using (7) we can write (5) as:

$$\xi^2 = \frac{\frac{1}{N}\sum_{i,j \in \Omega}(kn_{i,j} - k\overline{n})^2}{(k\overline{n})^2} = \frac{var(n)}{\overline{n}^2} \tag{8}$$

In (8), the CV depends only on the multiplicative noise, and it does not depend on the reflectivity.

The variance of a variable A can be written as:

$$var(A) = E(A^2) - E(A)^2 \tag{9}$$

Using (9) and (5) we can write:

$$\frac{var(Rn)}{E(Rn)^2} = \frac{1}{E(Rn)^2}[E((Rn)^2) - E(Rn)^2] \tag{10}$$

Developing (10) leads to:

$$\frac{var(Rn)}{E(Rn)^2} = \underbrace{\frac{var(n)E(R)^2}{E(Rn)^2}}_{First} + \underbrace{var(R)\frac{(var(n) + E(n)^2)}{E(Rn)^2}}_{Second} \tag{11}$$

In (11) the first term corresponds to the global CV. The second term is positive, it grows with the variance of the reflectivity. Thus, we can easily show that $\gamma \approx \xi$ in homogeneous areas and $\gamma \gg \xi$ at the edges. This property makes the CV a good edge detector for images affected by speckle.

4. The proposed stopping term

The traditional edge stopping term based on gradient has disadvantages. The first disadvantage is that the edge stopping function is never exactly zero and the moving curve may cross the boundaries of the object. A second disadvantage is that the edge detection based on gradient is not adapted to speckle. In images affected by multiplicative noise, the gradient detects the contours produced by the noise, resulting in too many small contours. This work addresses these problems by using a stopping term based on the coefficient of variation.

The stopping term in the level set is related to the coefficient of diffusion in the anisotropic diffusion. Both terms depend on the image gradient. In the level set it controls the motion of the moving curves, whereas in the anisotropic diffusion, the term controls the smoothing process.

Anisotropic diffusion is equivalent to a robust procedure that estimates a piecewise constant image from a noisy input image. The coefficient of diffusion in the robust anisotropic diffusion equation is based on an error norm and influence function. The formulation of robust anisotropic diffusion allows to adapt any robust error norm into the diffusion process. In [15] a coefficient of diffusion based on Tukey's biweight error norm has been proposed, to preserve sharp boundaries. The coefficient of diffusion is:

$$g(x,\sigma) = \begin{cases} \frac{1}{2}[1 - (\frac{x}{\sigma})^2]^2 & \text{if} \quad x \le \sigma \\ 0 & otherwise \end{cases} \tag{12}$$

An efficient coefficient of diffusion is proposed in [16] to filter images affected by speckle. It combines the advantages of (12) and the use of the coefficient of variation. Taking into account the characteristics of this coefficient of diffusion, we propose a new stopping criterion for the level set algorithm to segment ultrasound images. Our stopping term is:

$$g(\gamma)_{i,j} = \begin{cases} \left[1 - \frac{\gamma_{i,j}^2}{\gamma_s^2}\right]^2 & \text{if} \quad \gamma_{i,j} \le \gamma_s \\ 0 & otherwise \end{cases} \tag{13}$$

where $\gamma_{i,j}$ is the local CV and γ_s is a scale parameter based on the global CV. Edges correspond to pixels where the values of local CV is greater than the global CV.

Our stopping criterion (13) has two interesting properties: it is exactly equal to zero at the edges; and it is robust to speckle.

In order to calculate $\gamma_{i,j}$, we use the instantaneous coefficient of variation (ICOV) proposed in [12]. The ICOV expression is:

$$q_{i,j} = \sqrt{\frac{|(\frac{1}{2})||\nabla I_{i,j}||^2 - (\frac{1}{16})(\nabla^2 I_{i,j})^2|}{(I_{i,j} + (\frac{1}{4})\nabla^2 I_{i,j})^2}} \quad (14)$$

where $I_{i,j}$, ∇, ∇^2, $||\ \ ||$ and $|\ \ |$ are the image intensity at position (i,j), the gradient, laplacian, gradient magnitude, and absolute value, respectively. The derivation and discretization of (14) can be found in [17, 12].

In order to completely evaluate (13), we must calculate γ_s. In [16] the global coefficient of variation is calculated automatically as:

$$\gamma_s = \sqrt{5}\gamma_e \quad (15)$$

where γ_e is known as interception term. In [16] a robust estimation of this parameter is developed. The expression of the interception term is:

$$\gamma_e = c * med(|\gamma - med(\gamma)|) + med(\gamma) \quad (16)$$

where $c = 1.4826$ and γ is the matrix of the instantaneous coefficients of variation of the image.

5. Results

5.1. Synthetic images

In order to compare the effects of using a stopping term based on gradient or that based on ICOV, we experimented with a synthetic noisy image. Figures 1a, 1b, 1c show the edge detection using narrow-band level set with a gradient based stopping term. Figures 1d, 1e, 1f show the edge detection using an ICOV based stopping term. Both sequences show iterations 1, 150 and 300 respectively.

In figure 1, the moving curve does not suitably detect the objects when the stopping criterion is gradient based. Figure 1a contains the initial moving curve. In figure 1b the moving curve begins to enfold the objects of the image. In figure 1c the noise prevents stopping the evolution of the curve at the edges of the objects. In figure 1f, the previous problem disappears when using an ICOV based term.

Considering that the algorithm to solve (4) is extremely slow, an important improvement is obtained by using the stopping term adapted to speckle. We can observe that less iterations are required to detect the contours in the image. In addition, results presented in figure 1f, show that the new stopping term contributes to improve the precision of the contours.

5.2. Real ultrasound images

In order to compare the performance of our method, we used an ultrasound intra cavity image. The sequence of figures 2a-2j shows the edge detection using a gradient based stopping term. The sequence of figures 2k-2t shows the edge detection using an ICOV based stopping term. The 2 sequences show iterations 1, 20, 50, 80, 100, 150, 200, 250, 300 and 400 respectively.

In the first sequence, the presence of noise prevents the curve from stopping at the edges. With more iterations the moving curve disappears. In the second sequence of images, when the stopping function is adapted to speckle, an important improvement is observed. The stopping term is exactly equal to zero at the edges and the curve stops completely.

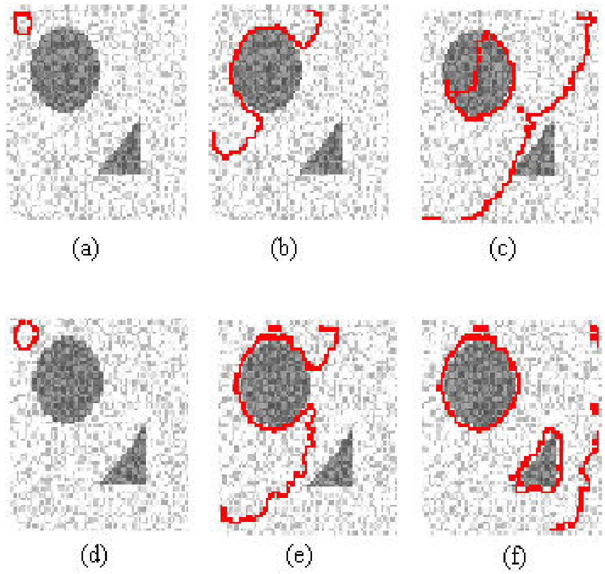

Figure 1. Results on synthetic noisy image

6. Conclusion

This paper presented a new stopping term adapted to speckle for the level set algorithm.

The classical edge stopping term based on gradient is not adapted to speckle and never equals zero, making the moving curve pass through objects boundaries.

Our stopping term is equal to zero at the edges. It is adapted to speckle. This prevents the moving curve from crossing the boundary of the cavities. In addition, the proposed stopping term reduces significantly the amount of iterations to detect the contours.

Thus, our stopping criterion brings significant enhancement in the contours detection of the heart cavities using level set.

The results of this study are promising. Future work will consider: a quantitative evaluation of the segmentation quality, and the use of other efficient level set methods for cardiac ultrasound image sequences.

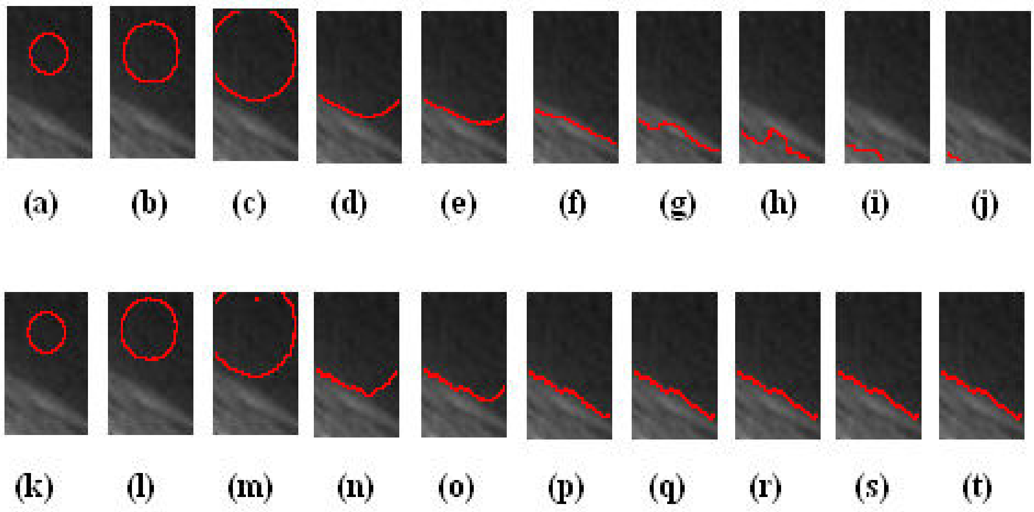

Figure 2. Results on ultrasound intra cavity image

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