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Robust boundary detection of left ventricles on ultrasound images using ASM-level set method

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Abstract. Level set method has been widely used in medical image analysis, but it has difficulties when being used in the segmentation of left ventricular (LV) boundaries on echocardiography images because the boundaries are not very distinguish, and the signal-to-noise ratio of echocardiography images is not very high. In this paper, we introduce the Active Shape Model (ASM) into the traditional level set method to enforce shape constraints. It improves the accuracy of boundary detection and makes the evolution more efficient. The experiments conducted on the real cardiac ultrasound image sequences show a positive and promising result.

Keywords: Level set method, image segmentation, active shape model

1. Introduction

Level set method has been widely used in image processing and computer vision. It was introduced by Sethian, et al [1] in the context of active contour (or snake) models [2-4] for image segmentation. In the traditional level set formulations, the level set function (LSF) typically develops irregularities during its evolution, which may cause numerical errors and eventually destroy the stability of the evolution [5]. The segmentation of left ventricular (LV) boundaries on echocardiography images is especially difficult. Echocardiography is one of the major imaging techniques to measure the heart functions [6]. The detection of the cardiac boundaries, especially left ventricular (LV) boundaries on echocardiography images, is crucial for the quantitative cardiac functional assessment. This task remains a challenging problem due to several reasons. Ultrasound is one of the noisiest methods among common medical imaging techniques, the signal-to-noise ratio is normal not very high, and also the boundaries are very often not distinguishable.

In order to solve the difficult segmentation problem of left ventricular (LV) boundaries, in this paper, the shape model information of the active shape model (ASM) scheme [7-9] is added in the level set method during the evolution. The ASM's advantage is that it is not based on a theoretical analytic

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model; rather it uses a statistical model that automatically learns from training data sets. In this paper this method is used to improve the traditional level set method by enforcing geometric constraints. The detection results for the left ventricles are shown in this paper, although the proposed method can be used for other segmentation purposes.

2. The proposed method

In this section, the formulation of enforcing geometric constraints of ASM to the traditional level set method is presented. We assume the dynamic parametric contour as $C(\mathrm{s},\mathrm{t}):[0,1]\times[0,\infty)\to R^2$, and s is a spatial parameter in $[0,1]$, and $\mathrm{t}\in[0,\infty)$ is a temporal variable, and we represent the LSF as $\phi(\mathrm{x},\mathrm{y},\mathrm{t})$.

We define the total energy function of the segmentation as

$$\mathsf{E}(\phi)=\mu\mathsf{R}_p(\phi)+\lambda\mathsf{L}_g(\phi)+\alpha\mathsf{A}_g(\phi)+\gamma\mathsf{S}(\phi) \tag{1}$$

Where $\mu>0$ is a constant, and $\mathsf{R}_p(\phi)$ is the distance regularization term as defined in the following:

$$\mathsf{R}_p(\phi)\triangleq\int_\Omega p(|\nabla\phi|)dx \tag{2}$$

Where p is a potential (or energy density) function, $p:[0,\infty)\to\mathrm{R}$. It is defined by

$$p(s)=\begin{cases}\dfrac{1}{(2\pi)^2}(1-\cos(2\pi s)), & \text{if } s\le 1\\ \dfrac{1}{2}(s-1)^2, & \text{if } s>1\end{cases} \tag{3}$$

$\mathsf{L}_g(\phi)$ is used to move the curve to the image edges, and it is defined by

$$\mathsf{L}_g(\phi)\triangleq\int_\Omega g(I)\delta_\varepsilon(\phi)|\nabla\phi|dx \tag{4}$$

By assuming ϕ as a contour $C:[0,1]\to\Omega$, the energy function $\mathsf{L}_g(\phi)$ can be regarded as a line integral $\int_0^1 g(\mathrm{C}(\mathrm{s}))|C'(\mathrm{s})|ds$. When ϕ locates in the object boundary, the energy $\mathsf{L}_g(\phi)$ will be minimized. Caselles, et al [10] introduced the function $\int_0^1 g(\mathrm{C}(\mathrm{s}))|C'(\mathrm{s})|ds$ for the first time, and the function is energy of a contour C in their proposed geodesic active contour (GAC) model.

$\mathsf{A}_g(\phi)$ is used to speed up the motion of the zero level contour during the level set evolution process:

$$\mathsf{A}_g(\phi) \triangleq \int_{\Omega} g(I) H_{\varepsilon}(-\phi) dx \tag{5}$$

Where H is the Heaviside function and

$$g(I) \triangleq \frac{1}{1+\left|\nabla G_{\sigma} * I\right|^{p}},\ p>1 \tag{6}$$

Where G_σ is a Gaussian kernel with a standard deviation σ and the I is the image. The convolution in the above equation is used to reduce the noise of the image. This function will take smaller values than others when the contour locates in object boundaries.

In above equations, H_ε and δ_ε are defined by

$$H_{\varepsilon}(x) = \begin{cases} \frac{1}{2}\left(1+\frac{x}{\varepsilon}+\frac{1}{\pi}\sin(\frac{\pi x}{\varepsilon})\right), & |x| \le \varepsilon \\ 1, & x > \varepsilon \\ 0, & x < -\varepsilon \end{cases}, \tag{7}$$

$$\delta_{\varepsilon}(x) = \begin{cases} \frac{1}{2\varepsilon}[1+\cos(\frac{\pi x}{\varepsilon})], & |x| \le \varepsilon \\ 0, & |x| > \varepsilon \end{cases}. \tag{8}$$

Normally ε takes the value of 1.5.

$\mathsf{S}(\phi)$ is used to model the difference between the current region shape and the mean shape ϕ_M as the results of a pre-training process in ASM. In this paper, it is defined by the ASM-based shape model as:

$$\mathsf{S}(\phi) \triangleq \int_{\Omega} (\phi - \phi_M)^2 \delta_w(\phi) dx \tag{9}$$

Where,

$$\delta_{w}(x) = \begin{cases} \frac{1}{2w}[1+\cos(\frac{\pi x}{w})], & |x| \le w \\ 0, & |x| > w \end{cases}. \tag{10}$$

It is used to define the narrow band along the region boundary and w is the width of the narrow band.

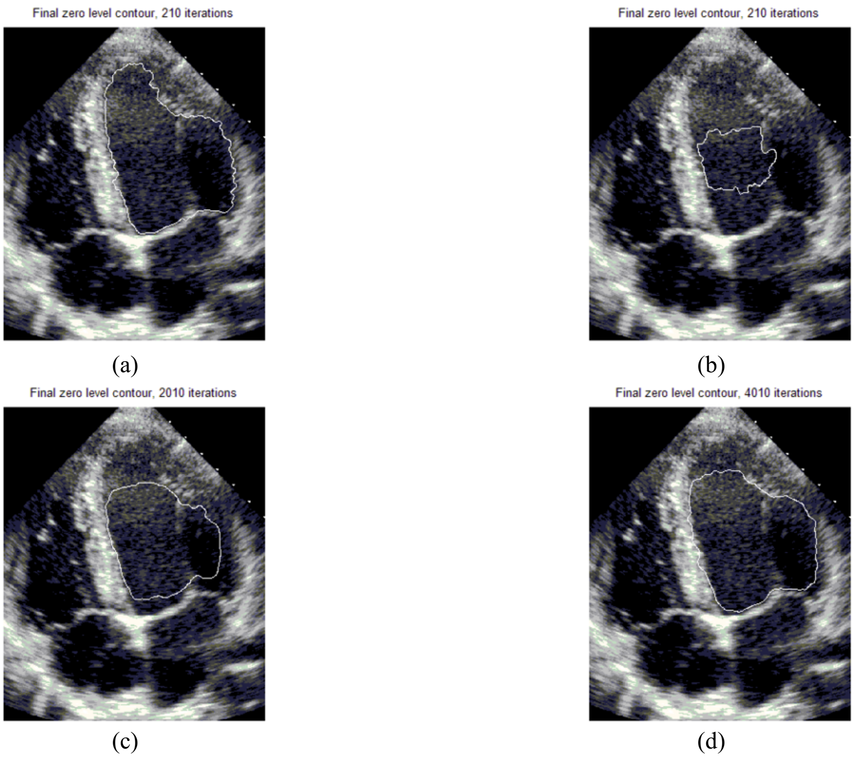
In calculus of variations, it is necessary to find the steady state solution of the gradient flow equation in order to minimize energy function.

$$\frac{\partial\phi}{\partial t} = -\frac{\partial \mathrm{F}}{\partial\phi}, \tag{11}$$

$$\begin{aligned}\frac{\partial\phi}{\partial t} &= \mu \mathrm{div}(d_p(|\nabla\phi|)\nabla\phi) + \lambda\delta_\varepsilon(\phi)\mathrm{div}(g\frac{\nabla\phi}{|\nabla\phi|}) + \alpha g\delta_\varepsilon(\phi) \\ &-2\gamma(\phi-\phi_M)\delta_w(\phi) - 2\gamma(\phi-\phi_M)^2\delta'_w(\phi)\end{aligned}. \tag{12}$$

And

$$\delta'_w(x) = \begin{cases} -\frac{1}{2w^2}\sin(\frac{\pi x}{w}), & |x| \le w \\ 0, & |x| > w \end{cases} \tag{13}$$



(a) (b) (c) (d)

Fig. 1. (a) The results of ASM-based level set method with 210 iterations; (b) the results of the traditional level set method with 210 iterations; (c) the results of the traditional level set method with 2010 iterations; (d) the results of the traditional level set method with 4010 iterations.

3. The results and discussion

The proposed ASM based level set method has been tested on many ultrasound image sequences, some of them are simulated images, and some of the experiments are based on real ultrasound images taken from Ultrasound diagnosis machines in hospitals.

Figure 1 shows the results of the ASM based level set methods on a real clinical Ultrasound image sequence. This sequence was acquired from a Philips iE33 Ultrasound machine on a real patient. Figure 1(a) illustrates the results with ASM-based shape model, Figures 1(b)-1(d) illustrates the results of the traditional level set method with different iterations. In Figure 1(a), it is easily seen that the results of the ASM-based level set method is pretty good. It almost perfectly detects the boundary. Comparing with the Figure 1(b), it is easily seen that the ASM-based method needs fewer iterations; and comparing with the Figures 1(c) and 1(d), it is easily seen that the traditional method couldn't evaluate the boundary very well, we found that the curves were not consistent with the boundaries and the computation needs with 4010 iterations. The level set method with ASM-based shape model in this paper is faster and more accurate than the traditional method. We have applied the ASM based level set method with 242 frames image, and the results are similar. There are also some issues to be improved: (1) In our proposed method, the shape model is important, if the shape model is very inaccurate, the results of this method will be largely influenced; (2) Because of using a signed distance function as the initial zero level set contour, the proposed method is not highly real-time; (3) the robustness of this method needs to improve. Further research is thus carried out for the clinical usages of the segmentation results.

4. Conclusion

Segmentation is a vital aspect of the medical imaging analysis. It aids in the visualization of medical data and diagnostics of various diseases. Extraction of such information from ultrasound images remains an open problem. ASM is a statistical model for the shape of objects that iteratively change to fit the corresponding objects in a new image. A new method is proposed, for the boundary detection of left ventricles, based on the introduction of ASM shape model into the level set method. The experiments have been carried out on the real cardiac ultrasound image sequences, and the outputs shown a positive and promising result. It should be pointed out that the proposed method still needs refinements and more tests are needed on Ultrasound images as well as intense comparisons of the proposed boundary detection algorithm with other methods.

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