Journal of Computers Vol. 27, No. 4, 2016, pp. 187-196
doi:10.3966/199115592016122704015

An Improved Adaptive Aorta Segmentation Algorithm Base on Level Set Method

Yan-Min Luo[1,2], Jun-Yang[2*], Pei-Zhong Liu[3], De-Tian Huang[3], Hong-wei Chen[4], Xiang-yu Luo[2], and Ren-cheng Zhang[1]

[1] College of Mechanical Engineering and Automation, Huaqiao University, Xiamen 361021, China
lym@hqu.edu.cn

[2] College of Computer Science & Technology, Huaqiao University, Xiamen 361021, China
657639637@qq.com

[3] College of Engineering, Huaqiao University, Quanzhou , Fujian 362021, China
pzliu@hqu.edu.cn

[4] Quanzhou First Hospital Quanzhou , Fujian 362021, China
chw120@163.com

Received 05 November 2015; Revised 27 January 2016; Accepted 13 February 2016

Abstract. Segmentation of aorta is very important in clinical diagnosis and medical quantitative analysis. The computed tomography (CT) image of aorta typically has small area and blurred boundaries, and the noise impact is serious. Therefore, it is difficult to segment the aorta using traditional methods. Being geometric active contour (GAC) model and Chan-Vase model has the unsatisfactory segmented results and inefficient curve evolution against weak boundary and intensity in-homogeneity images respectively, an improved variational level set image segmentation method is proposed. Our model consists of an external energy term that integrate the image information from both the gradient and region, And according to the characteristics of the shape of aorta region in CT images, circular formula is acted as the shape energy term, which can improve the segmentation accuracy. Finally, the self-adaptive shop function is added to avoid over-segmentation phenomenon and avoid waste time. The experimental results show that the new method proposed in this paper can segment aorta from the CT image accurately and efficiently, and it is robust to noise.

Keywords: aorta, Chan-Vese model, geometric active contour (GVA) model, image segmentation, level set, prior shape

1 Introduction

For the past few years, the spiral computed tomography (CT) multi-phase dynamic scanning is used widely in the diagnosis of aortic diseases and postoperative review. With the rapid development of computer technology, computer image processing technology has been widely used in the field of medical research, especially in the aspect of medical image diagnosis, it provides an effective supplementary measure [1]. The aortic image segmentation technique provide convenience for the quantitative analysis of radial artery and understanding the artery morphologic change. In the CT image of human body, the grayscale distribution of image contains region of background and region of interest. The significant diagnostic message is contained in region of interest. In spite of the message located on a very small plot in the whole image, its costs of error description are high. Therefore, the region of interest is the key point of medical image segmentation. Compared with other images, the complexity and variety of medical image makes the traditional segmentation method based on the underlying image information is hard to

* Corresponding Author

achieve good segmentation results. The emergence of the level set method promotes the development of the active contour model. The combination of level set method and active contour model can overcome a lot of inherent vice of the traditional snake model and expand the applications of active contour model.

The level set method is divided into two classes: the edge information based level set method [1] and the region based level set method [2]. The edge information based level set method mainly depends on the edge strength, it can segment the image with un-uniform brightness. But this method is sensitive to initialization and noise, and it is easy to be out of bounds for the weak edges of the image.

The region based level set method, represented by the Chan-Vase model [3], defines the region description mostly based on “brightness consistency” hypothesis. It is difficult to segment the images with un-uniform brightness effectively. The block smooth model is a typical method for the images with un-uniform brightness. This model segments the image by boiling down to the problem which is in search of piece-wise smooth functions of optimization similar image. So this method can reduce the influence of un-uniform brightness. But this method is sensitive to the initialize and obtains a high complexity. Li et al. put forward the local binary fitting (LBF) model [4], which translates the segmentation problem into looking for the optimum cure and its LBF function, whereby the fitting function is brightness fitting of local region of curve’s both sides. The LBF model has the stronger localization property, and it can be efficient to segment the weak boundary target. However, the localization property also leads to the model falling into local optimum. Wang et al. put forward the local Chan-Vese model [5] (LCV), which adds the local fidelity term into the CV model, and enhances the gray contrast between the target and background of the image by performing the differential operation between the convolution image and the original image

In recent years, adding the prior information of the target is added into active contour models has become the important research content of image segmentation [6]. Schmid et al. [7] used statistical shape model to segment the bone in the MRI(magnetic resonance image); Chan et al. [8] added the prior shape information to zero level set instead of level set function, and took the distance between prior shape and zero level set as shape restriction or as the weight of curve length in CV model which can constraint the evolution of the level set function. Chen el ct. [9] trained the data which has been segmented to get the deformable model of organ, and set up segmentation value function based on the Bayesian framework. Some scholars used the known shape as the prior energy term to segment the image. Those methods can get a good segmentation effect for special image [10-11].

2 The Level Set Method Description

The level set method implicitly defines the cure as the level set of curve function in high-dimensional space, that is to say the set of the points with the same function value can implicitly calculate the contour curve by the evolution of the level set function curve. The key of the method is to set up an energy model firstly. The internal term and external energy of the energy mode are all expressed by level set function. Then the energy function is minimized by using the variational method, on which we can get the partial differential equation (PDE) of level set evolution.

Geodesic active contour (GAC) model [12] is the model based on curve evolution theory and level set method which is put forward by Caselles et al. In 1997, GAC is considered as key breakthrough of the PDE method applied in image segmentation. Supporting φ is the level set function, the curve evolution PDE of GAC model is expressed as the following:

$$\frac{\partial \varphi}{\partial t} = [gk - \nabla g \circ N] | \nabla \varphi | = | \nabla \varphi | \, div[g \frac{\nabla \varphi}{\nabla \varphi}] \quad \textbf{(1)}$$

Where g is the describing function of marking image edge feature, k is mean curvature, N is the normal vector of curve, ∇ is gradient operator. In view of the curve evolution problem derived from the energy functional of the curve, the variational GAC model can be obtained by using the variational method to obtain the curve evolution PDE. The variational method can be used to obtain it variational PDE, which is showed in formula (2).

$$\frac{\partial \varphi}{\partial t} = \delta_{\varepsilon}(\varphi) div[g \frac{\nabla \varphi}{| \nabla \varphi |}] \quad \textbf{(2)}$$

GAC model is one of the most popular edge-based method, which can deal with the topological change of the curve movement freely without any external control condition. But there are still some disadvantages. Such as, if just using the local edge information of the image, For the edge of the segmentation object is not always the ideal step edge, it is difficult to segment the homogeneous region in the edge blurred image. Furthermore, when the target in the image has deeper concave boundary, GAC model may make the evolution curve stop at a local minimum which is not consistent with the boundary of the target.

Chan and Vese put forward an image segmentation method based on simplified Mumford-Shah model and level set which is called brimless active contour model, and named C-V model. It is a typical applications in variational level set models.

Let the domain of image to be Ω, the profilogram C divided the image into a number of approximation regions. Supporting Φ is high-dimensional smooth level set function. By updating Φ constantly, the level set method evolves the profilogram C which implied in Φ.

The C-V model is based on the Mumford-Shah level set model. Supporting that image $I(x,y)$ is divided into two homogeneous regions by the contour curve, one is the target ω_0 (inside of curve C) and the other is the background ω_1 (outside of curve C). Let c_1 is the average gray of target ω_0 and c_2 is the average gray of background ω_1. The energy function of C-V model is showed in formula (3).

$$\mathrm{E}^{\mathrm{CV}}(c_1,c_2,C)=E_l+E_{region}=l\cdot Length(C)+\lambda_1\cdot\int_{inside(C)}|I(x,y)-c_1|^2dxdy+\lambda_2\cdot\int_{inside(C)}|I(x,y)-c_2|^2dxdy \quad \textbf{(3)}$$

Where *Length(c)* represents the length of closed contour C. μ, λ_1, λ_2 are positive constant values which are the weighting coefficient of each energy term. Generally μ=0, λ_1=1 and λ_2=1. On the formulas discussed above we know that if the closed curve C is located outside of real boundary, then the level set function $\Phi<0$, while if the closed curve C is located inside of real boundary, then the level set function $\Phi>0$, in addition if the closed curve C is exactly the real boundary, then the level set function $\Phi=0$. Therefore the goal of image segmentation is to search for the closed contour C which can get the minimum of energy function E. We define it to be $+\lambda_1\int_\Omega|u_0(x,y)-c_1|^2H(\phi(x,y))dxdy$.

Because the C-V level set method takes full advantage of image's global information, it can get global optimization segmentation results by the optimization of energy function,. The C-V level set model is based on the assumption that image is piece-wise smoothness, so this method introduced Heaviside function *H(z)* and Dirac function *δ(z)* to normalize *E(C,c1,c2)* which are showed in formula (4) and (5).

$$+\lambda_2\int_\Omega|u_0(x,y)-c_2|^2(1-H(\phi(x,y)))dxdy \quad \textbf{(4)}$$

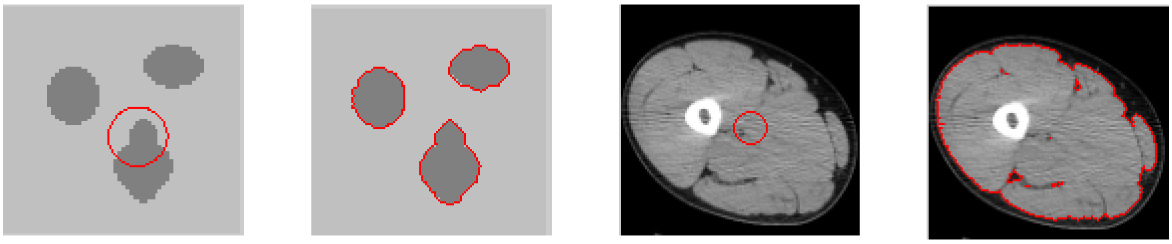
$$\delta(z)=\frac{d}{dz}H(z) \quad \textbf{(5)}$$

Let zero level set $\Phi 0$ of level set function Φ to represent closed contour C. The function of Heaviside function *H(z)* is to divide the evolution region, and the function of Dirac function *δ(z)* is to limit the evolution to get the value around the zero level set function. From the above, the energy function can be expressed by formula (6).

$$E^{CV}(c_1,c_2,\phi)=l\int_\Omega\delta(\phi(x,y))\,|\nabla\phi(x,y)|\,dxdy+\lambda_1\int_\Omega|u_0(x,y)-c_1|^2H(\phi(x,y))dxdy \quad \textbf{(6)}$$

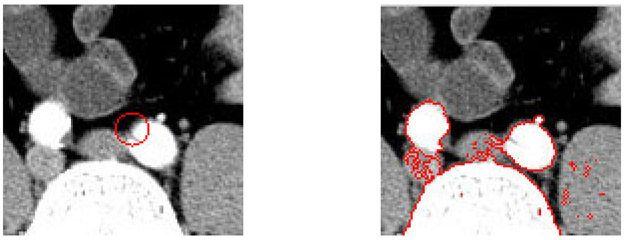
$$+\lambda_2\int_\Omega|u_0(x,y)-c_2|^2(1-H(\phi(x,y)))dxdy$$

The C-V model is widely used as the region-based level set. But if the edge information is not accurate, the segmentation results would be inaccuracy. Fig.1 and Fig. 2 show some segmentation results of C-V model to the image with sharp edge and weak edge, which indicated that the C-V method can segment the image with sharp edge well, but can not get the exact result for the image with weak edge.



(a) initial contour (b) C-V method (c) initial contour (d) C-V method

Fig. 1. Image with the sharp edge



(a) Initial contour (b) C-V method

Fig. 2. Image with weak edge

Therefore, this paper introduces the weak edge features of aorta CT image into C-V method, and put forward a new segmentation method for aorta CT images by combining the edge information and region information of the image.

3 The Aortic Segmentation Based on Shape Restriction

3.1 The shape energy term

For image segmentation based on level set method, if the shape of the target to be segmented in the image is very complex, it can restrain convergent shape of morphable model and make the curve evolution result to be consistent with the shape prior characteristics and solve the problem of disturbing from non-target region by adding the shape prior information into level set method. Leventon proposed a shape model structure of principal component analysis and signed distance function (SDF) [13]. In Shi and William's study, a fast level set method in real time was proposed. But these methods are computationally inefficient [14].

This paper adds circular shape constraint term to restrain the contraction shape of deformable model by reason of that aortic blood vessels are generally circular or elliptical. In this way, the evolution of the curve is in accordance with prior circular characteristic, which can also avoid the interference of non-target area.

So the segmentation energy function E should be turned into $E = E_{seg} + E_{shape}$. Where E_{shape} is the shape constraint term, which is usually expressed implicitly by SDF. Supporting Ω is the image domain, ϕ is the evolving curve, ϕ_s is the SDF of prior shape. The prior shape energy term can be defined by the similarity between ϕ and ϕ_s, which is showed in formula (7).

$$E_{shape}(\phi,\phi_s) = \iint_{\Omega} (H(\phi) - H(\phi_s))^2 \, dxdy \tag{7}$$

The shape term can be expressed by the equation of a circle which is expressed by(a,b,r,θ). So the shape model is showed in formula (8):

$$\psi = 1 - \sqrt{\frac{[(x-x_0)\cos\theta + (y-y_0)\sin\theta]^2 + [-(x-x_0)\sin\theta + (y-y_0)\cos\theta]^2}{a_0^2}} \tag{8}$$

where (x_0, y_0) represents the central point of circular constraint term, θ is rotation angle, a_0 represents zoom factor of radius. To simplify equation, this paper define A and B as following:

$$A=(x-x_0)\cos\theta+(y-y_0)\sin\theta \tag{9}$$

$$B=-(x-x_0)\sin\theta+(y-y_0)\cos\theta \tag{10}$$

Taking formula (9) and formula (10) into formula (8), the model of circular shape constraint term can be defined as formula (11).

$$\psi=1-\sqrt{\frac{A^2+B^2}{a_0^2}} \tag{11}$$

3.2 The modified C-?V level set model

According to the problem of weak edge and deep depression boundary in image segmentation, this paper put forward an image segmentation method based on the combinations of edge information and region information, and also add the prior knowledge about object shape to t energy function. Which can make the proposed method both have the advantage GAC model and the advantage of C-V model.

Firstly, based on the symbolic distance function this paper defines an internal energy term which use the energy penalty term as internal constraint energy term. The design of energy penalty term is based on the ref. [4] which is proposed by professor Li. Formula (12) shows the an internal energy term.

$$P(\varphi)=\mu\iint_{\Omega}(|\nabla\varphi|-1)^2\,dxdy \tag{12}$$

Secondly, The external energy term is composed of two parts. One is image edge feature function which is defined by gradient information of image edge. For the image *I*, the image edge feature function is $g(|\nabla\varphi|)=e^{-|\nabla G_\sigma * I|^2}$, where g is the edge indicator function, G_σ showed in formula (13) is Gaussian smooth Kernel Function with the scale parameter σ.

$$G_\sigma(u)=\frac{1}{(2\pi)^{\frac{n}{2}}\sigma^n}e\frac{-|u|^2}{2\sigma^2}. \tag{13}$$

The other is based on the image global region information which we use the C-V model to define it. We have discussed in section 2.

Finally, the circular shape energy term which was presented in section 3.1 is added to the C-V model. Therefore, the energy function is composed of three item: length term, global term and shape term, which is showed in formula (14):

$$E=E_L+E_{in}+E_{out}+E_{shape} \tag{14}$$

where the length term EL can be defined as *Length*(*C*), which based on the C-V model theory discussed in section 2. The formula of *Length*(*C*) is showed in formula (15)

$$\begin{aligned}Length(C)&=Length(\phi=0)\\&=\iint_{\Omega}\delta(\phi(x,y))\,|\nabla\phi(x,y)|\,dxdy\\&=\iint_{\Omega}|\nabla \mathrm{H}(\phi(\mathrm{x,y}))|dxdy\end{aligned} \tag{16}$$

and the global term includes internal energy term and external energy term. The internal energy term is defined as:

$$E_{outside}=E_{edge}+E_{region} \tag{17}$$

where

$$E_{edge} = \iint_{\Omega} gH(\phi)dxdy \tag{18}$$

and

$$E(\phi, C_1, C_2) = \mu \iint_{\Omega} \frac{1}{2}(|\nabla\phi(x,y)|-1)^2 dxdy + l\iint_{\Omega}\delta(\phi(x,y))|\nabla\phi(x,y)|dxdy\,, \tag{19}$$

where

$$v\iint_{\Omega} gH(\phi)dxdy + \ \lambda_1 \iint_{\Omega} |I(x,y)-C_1|^2\ H(\phi(x,y))dxdy + \tag{20}$$

$$\lambda_2 \iint_{\Omega} |I(x,y)-C_2|^2 (1-H(\phi(x,y)))dxdy \ \ +\lambda_3 \iint_{\Omega} (H(\phi)-H(\phi_s))^2 dxdy \tag{21}$$

Combining with the preceding shape energy term, the final and complete energy formula is shown in formula (22).

$$\begin{aligned} E(\phi, C_1, C_2) = {} & \mu \iint_{\Omega} \frac{1}{2}(|\nabla\phi(x,y)|-1)^2 dxdy + l\iint_{\Omega}\delta(\phi(x,y))|\nabla\phi(x,y)|dxdy \\ & v\iint_{\Omega} gH(\phi)dxdy + \ \lambda_1 \iint_{\Omega} |I(x,y)-C_1|^2\ H(\phi(x,y))dxdy + \\ & \lambda_2 \iint_{\Omega} |I(x,y)-C_2|^2 (1-H(\phi(x,y)))dxdy \ +\lambda_3 \iint_{\Omega} (H(\phi)-H(\phi_s))^2 dxdy \end{aligned} \tag{22}$$

The level set function of image to be segmented *I(x,y)* can be defined by formula (23).

$$I(x,y) = C_1 H(\phi(x,y)) + C_2(1-H(\phi(x,y))) \tag{23}$$

To get the SDF which is expressed by level set function *Φ*, This paper introduces approximate regularized Heaviside function *H*(*z*) and Dirac function *δ*(*z*) to replace the two function mentioned at section two. This two functions are defined as the followings:

$$H_\varepsilon(z) = \begin{cases} 1 & z \prec -\varepsilon \\ 0 & z \succ \varepsilon \\ \frac{1}{2}(1+\frac{2}{\pi}\arctan(\frac{z}{\varepsilon})) & |z| \le \varepsilon \end{cases} \tag{24}$$

$$\delta_\varepsilon(z) = \begin{cases} 0 & |z| \succ \varepsilon \\ \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2+z^2} & |z| \le \varepsilon \end{cases} \tag{25}$$

Finally, the level set evolution equation can be obtained by solving the Euler-Lagrange equation of energy function, which is showed in formula (26).

$$\frac{\partial\phi}{\partial t} = \mu(\nabla^2\phi - div(\frac{\nabla\phi}{|\nabla\phi|})) + \delta(\phi)[l div(\frac{\nabla\phi}{|\nabla\phi|}) - vg(x,y) - \lambda_1(I(x,y)-C_1)^2 + \lambda_2(I(x,y)-C_2)^2 + \lambda_3\phi_s] \tag{27}$$

where, ϕ_s is defined as

$$\phi_s = r^2 - (x - x_0)^2 - (y - y_0)^2 \tag{28}$$

The r in formula (28) is circular constraint term, and its update mode is showed in formula (29).

$$r(\phi) = \sqrt{\frac{\int_\Omega H(\phi)dxdy}{\pi}} \tag{29}$$

where (Δt , y_0) is the coordinate of regional node, and its update mode is showed in formula (30) and (31).

$$x_0 = \frac{\int xH(\phi)dxdy}{\int H(\phi)dxdy} \tag{30}$$

$$y_0 = \frac{\int yH(\phi)dxdy}{\int H(\phi)dxdy} \tag{31}$$

The update mode of gray average C1 and C2 in every iteration can be defined respectively as:

$$C_1 = \frac{\iint_\Omega I(x,y)H(\phi(x,y))dxdy}{\iint_\Omega H(\phi(x,y))dxdy} \tag{32}$$

$$C_2 = \frac{\iint_\Omega I(x,y)(1 - H(\phi(x,y)))dxdy}{\iint_\Omega (1 - H(\phi(x,y)))dxdy} \tag{33}$$

3.3 The realization process of aortic CT image segmentation algorithm

Part 3.2 has deduced the SDF of level set model which combines the edge information and region information and also includes the circular prior energy term. This part introduces the process of the proposed segmentation algorithm, the process is expressed as the followings:

Step 1: Image preprocessing. Because of the complex imaging reason of CT image, there are should exist many noise in CT image. The proposed algorithm applies the median filter algorithm to wipe off the noise in the precondition to make the image be more smooth.

Step2: Setting initial curve ϕ_0 as the initial level set function. The algorithm chooses circle as the initial curve, and the radius of the initial curve is decided by size of the image.

Step 3: Setting the values of parameters. Which include time step Δt, the coefficient of length term *l*, internal energy term control parameter μ, external energy term control parameter v, λ_1, λ_2, shape constraint term control parameter λ_3 and the number of iterations *n*.

Step 4: Iterating level set function ϕ_0 by using gradient descent.

Step 5: Extracting the zero level set, the evolution curves, from the level set function.

4 The Design of Self-Adaption Stop Function

During the evolution of level set, the evolution curve will be split according to the distribution of the target in the image, and finally approach to the target contour. Ideally the evolving of the curve would shop at the actual contour. But in practical application, we should control the evolving of the curve. Therefore how to control the evolving is important to the proposed algorithm.

According to the global term definition, the value of the global term is continuously falling during the evolving of the curve, and the actual contour is the solution when global term reaches the minimum value.

In this paper, we control the evolving by testing the difference of the evolving curve lengths between two adjacent evolution. we define difference to be $|L(C(t))-L(C(t-1))|$, where L(C(t)) is the length of the evolving curve in the t^{th} evolution, and $L(C(t\text{-}1))$ is the length of the evolving curve in the $(t\text{-}1)^{th}$ evolution. Here we use the Number of pixels in evolution curve to evaluate the length of the evolving curve. The evolution speed of the curve should slow down when the curve is approaching to actual object contour, and the difference between $L(C(t\text{-}1))$ and $L(C(t\text{-}1))$ will tend to 0 or the approximately constant. Based on this feature we design the termination criterion of level set evolution. When the absolute value of the curve length difference is always less than the threshold ζ which was set in advance, the evolution of level set should shop. Because of the complexity of image, the speed of evolution is possible to slow down for the moment before the curve approaching to the actual contour, thus the condition will be met. In practice, the value of the threshold is flexible, and generally ζ is a smaller number, while T should be a little larger number. In the following experiments, because segmented regions is smaller, the value of ζ was set to 2, and the value of T was set to 5.

Fig. 3 and Fig. 4 show the segmentation results and the iteration times of the proposed algorithm with self-adaption stop function and without self-adaption stop function respectively.

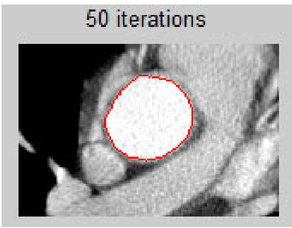


Fig. 3. The iteration times without self-adaption

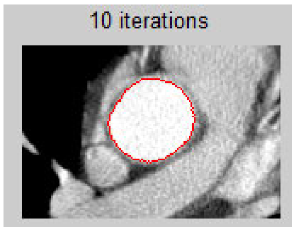


Fig. 4. The iteration times with self-adaption

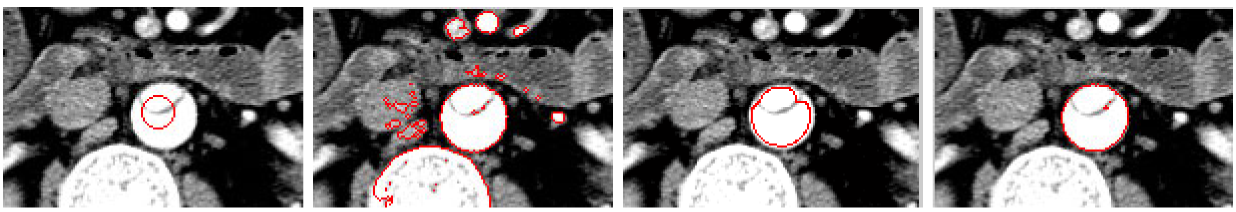
According to the results above, the method with self-adaption stop function can not only reduce the experimental time but also guarantee that the active contour is close to the real edge of the target.

5 Experiment and Analysis.

To verify the validity and effectiveness of the proposed algorithm, we use the algorithm to segment multiple images and compare the results with the traditional C-V model and LBF model [4]. The experimental data are the really CT images of patients with cardiovascular which we taken from hospital.

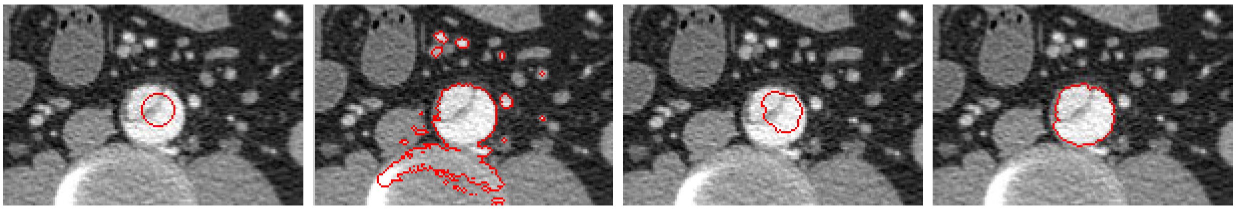
Because the size of CT images in medicine are fixed, which is 512*512 pixels. While size of the object we want to segment is smaller. Therefore we use coordinate cutting method to get the region of interest which includes the whole aortic area. In the experiments, the initial contour is defined as circle. The length of the initial contour's radius is set to 10, and time step is set to 0.1. The corresponding model of formula (21) is used to segment the aortic. There are many coefficient in formula (21) such as l, μ, v, λ_1, λ_2, λ_3. Among them l is the size ratio of length term, *μ is the coefficient of internal energy term, v, $\lambda 1$, and $\lambda 2$ are the coefficients of external energy term, and $\lambda 3$ is the coefficient of circle constraint energy term.* The value of those coefficient is important to the algorithm. By repeated experiments we select the most suitable value for our experiment, their values are μ=1, l=0.1*255*255, v=0.5, λ_1=0.5, λ_2=1, λ_3=1.

For each CT data, it contains a large number of images. We take several typical results from the series of CT images to show the results of the experiment. The experimental results are showed in Fig. 6~Fig. 8.



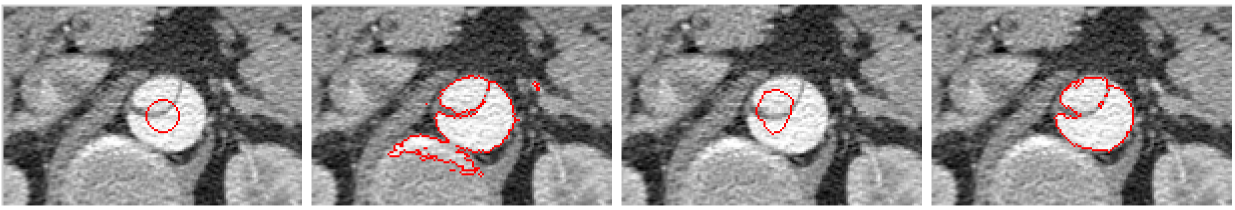
(a) The initial contour (b) C-V method (c) LBF method (d) The proposed method

Fig. 5. The CT image with clear outline of aorta and small noise



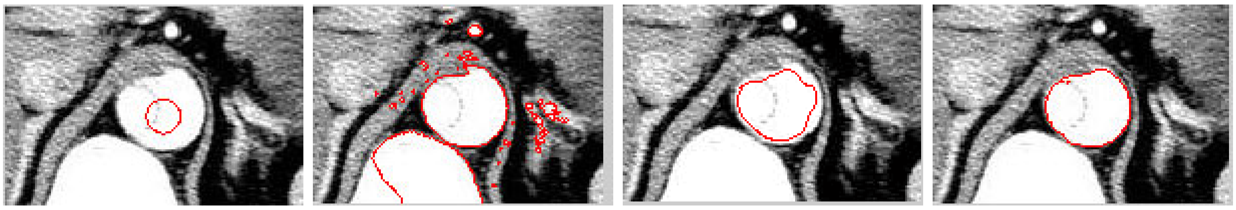
(a) The initial contour (b) C-V method (c) LBF method (d) The proposed method

Fig. 6. The edge blur CT image with noise



(a) The initial contour (b) C-V method (c) LBF method (d) The proposed method

Fig. 7. The CT image with close gray value between aorta and the background



(a) The initial contour (b) C-V method (c) LBF method (d) The proposed method

Figure 8. The CT image with part of aorta being covered

According to different characteristics, we divide the experimental images into four groups. Fig. 5 shows the results of the CT image with clear outline of aorta and small noise, Fig 6. shows the results about the edge blur CT image with noise, Fig 7. shows the results of the CT image with close gray value between aorta and the background, and Fig. 8 shows the results about the CT image with part of aorta being covered. The red circle in the initial contour of each group is the segmented images with The picture (a) in each group are the segmented image, the circle on which is the initial contour. The picture (b) in each group are the segmentation results of traditional C-V model level set method. The picture (c) in each group are the segmentation results of LBF model level set method. And the picture (d) in each group are the segmentation results of the proposed method. We set the number of iterations as 50. It can be found by comparing the results that the traditional C-V model level set method would occur over-segmentation phenomenon under the same number of iterations. While for the proposed method for it adds the shape bound term into the energy function which can make the evolution curves stay on the edge of the target exactly. In addition the proposed method design the self-adaption shop function, which can avoid the over-segmentation and improve the efficiency of the algorithm effectively. The iteration number and segmentation result of each method also shows that the convergence rate and segmentation accuracy of the proposed method are higher than LBF model level set method.

6 Conclusions

This paper studies the problem of segmentation of the aorta in CT images. According to the characteristic of CT image of aorta the C-V model level set method, this paper proposed a C-V level based image segmentation method which combining not only the edge feature but also regional feature. The experiments show that the proposed method can efficiently utilize the edge and region information of the image to be segmented, and is able to segment images with weak boundaries. In addition, the proposed algorithm adds circle as the shape energy term to the energy function which can exclude the interference from non-target region. We compare the proposed algorithm with other algorithms and the results show that proposed algorithm has good performance on the segmentation of aortic region in CT image. In the future research we Will further improve the robustness of the algorithm, and Widely spread it in the field of medical engineering application.

Acknowledgment

This work was supported by the Talent project of Huaqiao University (No. 14BS215), National Natural Science Foundation of China (No.61170028), Quanzhou scientific and technological planning projects of Fujian, China (2015Z120).

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