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Procedia Engineering 15 (2011) 2634 – 2638

Procedia Engineering

www.elsevier.com/locate/procedia

Advanced in Control Engineering and Information Science

Adaptive Medical Image Segmentation Algorithm Combined with DRLSE Model

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Abstract

The distance regularized level set evolution model proposed recently which uses Gaussian filter to reduce the image noise will yield blurred image edges. Besides, the model still can't segment adaptively. To slove these problems, we adopt regularized P-M equation filter which can remove the noise while preserve edge information. On the other hand, gradient informarion which depends on inward and outward area's curve is used to improve the direction of the unit normal vector. As a result, the curve can realize adaptive evolution inwards or outwards. In the end, the modified algorithm is applied to accurately extract the medical image's contour, and greatly reduce computational cost.

Keywords: variational level set; regularized P-M equation; unit normal vector; geodesic active contour; image segmentation

1. Introduction

The geodesic active contour(GAC) model without free parameters[1] has been extensively used in edge detection,medical image segmentation and so on. In Chunming Li et al.'s preliminary work,they proposed a variational level set formulation[2],which not only eliminated the need for reinitialization,but also greatly improved the efficiency of the algorithm. However, the function of the penalty term would lead the diffusion rate to tend to infinity. According, Chunming Li et al. proposed a new model,which was called distance regularized level set equation[3].By improving the function of the penalty term,the diffusion rate become a bounded constant,and sufficient numerical accuracy was realized. Nevertheless, this new model still has some disadvantages:

(1) The single scale of Gaussian filter has the contradiction of reducing the noise and keeping the edge of images. The DRLSE model use Gaussian filter to reduce the image noise, whereas it will yield blurred image edges.

(2) It needs to determine the constant evolution speed's symbol of the model artificially according to the position of initial curve. As a result, the model can not segment adaptively.

To slove these problems, this paper adopt regularized P-M equation filter which can remove the noise while preserve edge information. Meanwhile, according to the initial contour's position, the inside or

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doi:10.1016/j.proeng.2011.08.495

outside gradient modulus imformation of the initial curve is used to improve the direction of the unit normal vector adaptively. Consequently, the curve can realize adaptive evolution inwards or outwards. In the end of this paper, we apply this improved algorithm to the heart's MRI image and extract the contour of heart.

2. DRLSE Model

The geodesic active contour(GAC) models without free parameters, determined the active contour by minimizing the following "energy" fonctionelle:

$$L_R(C)=\int_0^{L(C)} g(|\nabla I[C(s)]|)ds$$

Chunming Li et al. introduced an internal energy $R_P(u)$ which was also called penalty term according to the characteristics of symbol distance function, and added it to the "energy" fonctionelle:

$$R_P(u)=\int_\Omega p(|\nabla u|)dx \tag{1}$$

The penalty term forced the curve to evolve near the signed distance function, thus in the course of curve evolution,it completely eliminated the need of the costly reinitialization procedure.

In Eq. 1, where $p=p_1(s)=1/2(s-1)^2$ had an only minimum point at $s=1$. According to the following gradient flow: $\frac{\partial u}{\partial t}=\mu div(d_p(|\nabla u|)\nabla u)$, where $d_p(s)=p'(s)/s \;=1-(1/s)$. According to the physical background of diffusion process,it was known that this equation is a diffusion equation,and the diffusion rate is $D=\mu d_p(|\nabla u|)$. According to the function of $d_p(s)$, when $|\nabla u|$ is close to 0, the diffusion rate may affect the numerical accuracy.

To avoid this problem, Chunming Li et al. introduced the function $p_2(s)$ which has two minimum points:

$$p_2(s)=\begin{cases}\frac{1}{(2\pi)^2}(1-\cos(2\pi s)) & s\le 1\\ \frac{1}{2}(s-1)^2 & s\ge 1\end{cases}$$

It is easy to verify that $d_p(s)=p_2{'}(s)/s$ satisfies $|d_p(s)<1|$ and $\lim_{s\to 0} d_p(s)=\lim_{s\to\infty} d_p(s) \;=1$ .The diffusion rate $|D|\le\mu$ is a bounded constant, and is avoided to go to infinity which is defined by $p_1(s)$, so as to improve numerical accuracy. The total energy functional:

$$E(u)=\mu\iint_\Omega p_2(|\nabla u|)dxdy+\lambda\iint_\Omega g|\nabla H(u)|dxdy+c\iint_\Omega[1-H(u)]gdxdy$$

where $\lambda>0$ and c is constant. H is the Heaviside function, and δ is the univariate Dirac function.

The steepest descent process for minimization of the total energy functional is the following gradient flow:

$$\frac{\partial u}{\partial t}=\mu div(d_{p_2}(|\nabla u|)\nabla u)+\lambda\delta(u)div(g\frac{\nabla u}{|\nabla u|})+cg\delta(u)$$

where $g=1/(1+|\nabla G_\sigma * I|^2)$,and G_δ is the Gaussion Kernel with standard deviation δ .This new model was called Distance Regularized Level Set Evolution(DRLSE).

3. The improvement of DRLSE

3.1. Isotropic nonlinear diffusion filter

In order to remove the image noise while preserve edge information,we adopt regularized P-M equation filter[4-5]:

$$\begin{cases} \frac{\partial I(x,y,t)}{\partial t} = div\left[g(|\nabla I_\delta|)\nabla I \right] \\ I(x,y,0) = I_0(x,y) \end{cases}$$

where $I_\delta(x,y,t) = G_\delta * I(x,y,t)$,and $g(|\nabla I_\delta|)$ is the edge stop function. It uses the image gradient modulus while filters the image noise, so as to filter the nosie together with image edge detection. As a result, it reserves the image edge while removes the image noise. Besides, it combines the single scale of Gaussian smooth with regularized P-M equation. It uses Gaussian to smooth the image firstly, finds out the filtering image's gradient modulus, and then uses regularized P-M equation to get the image which is smoothed with isotropic nonlinear diffusion filter.

3.2. Adaptive evolution model

In GAC model,if the initial curve surrounds the target boundary, the curve evolution requires to shrink, and then the constant speed is defined as $c>0$; if the initial curve is inside of the target boundary, it requires the curve evolution to expand outwards, and then the constant speed is defined as $c<0$. Therefore,once we decide the constant's symbol, the curve can evolve in one direction. It needs us, to define the constant's symbol artificially according to the position of initial contour. That is to say, it can not realize segmentation adaptively.

According to the knowledge of planar curve, the unit normal vector of the level set can be expressed as:

$$N = \pm \frac{\nabla u}{|\nabla u|} \tag{2}$$

When $u(x,y)$ is inside of the zero level set, the symbol of $u(x,y)$ is negative; when $u(x,y)$ is outside of the zero level set, the symbol of $u(x,y)$ is positive. So the unit normal vector's symbol is negative, conversely, the unit normal vector's symbol is positive. This makes the direction of the normal vector always point to the internal closed curve. According to the GAC model:

$$\frac{\partial C}{\partial t} = g(c+\kappa)N - (\nabla g \cdot N)N \tag{3}$$

All the two parts of Eq. 3 contain the curve's unit normal vector. According to the analysis of the GAC model's behavior, we know the curve's movement is driven by the unit normal vector'direction. Thus we can alter the initial function of $u(x,y)$, which can lead the inward normal vector's direction inwards or outwards, thereby guide the curve's movement inwards or outwards.

The image edge's gradient changes greatly, and the image gradient modulus is also large. If the target object waiting for segmentation is inside the evolution curve, there is both object and image backtround inside of the curve, and the gray distribution is complex. Therefore, the inside of the curve's average gradient modulus is larger than the outside. If the target object waiting for segmentation is outside the evolution curve, the inside of the curve's average gradient modulus is smaller than the outside accordingly [6]. According to Chunming Li et al.'s model, the function $u(x,y)$ is defined as follows:

$$u(x,y)=\begin{cases} -c_0 & (x,y)\in inside\ of\ C_0 \\ 0 & (x,y)\in C_0 \\ c_0 & (x,y)\in outside\ of\ C_0 \end{cases}$$

where c_0 is a constant, and C_0 is the initial curve. Therefore, we define adaptive function $u'(x,y)$ as follows:

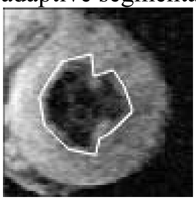
$$u'(x,y)=\begin{cases} u(x,y) & D_{\text{int}}>D_{ext} \\ -u(x,y) & D_{\text{int}}<D_{ext} \end{cases}$$

where D_{int} is the average of the image's gradient modulus of the inward region of the evolution curve, and D_{ext} is the average of the image's gradient modulus of the outward region of the evolution curve. Therefore, if the target object waiting for segmentation is inside the evolution curve, $D_{\text{int}}>D_{ext}$, $u'(x,y)=u(x,y)$, the symbol of Eq. 2 is negative, the direction of the normal vector points to the internal curve, and the curve evolve inwards; if the target object waiting for segmentation is outside the evolution curve, $D_{\text{int}}<D_{ext}$, $u'(x,y)=-u(x,y)$, the symbol of Eq. 2 is positive, the direction of the normal vector points to the external curve, and the curve evolve outwards.

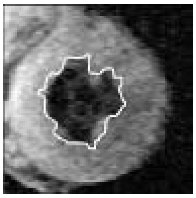
4. Result of the experiment

In medical image, the nidus's contour information is a very important characteristic information. The extracted contour can help doctors to quantitate the nidus, analyse the disease, and induct correct diagnosis plan. Because medical images containe strong noise, it will yield blurred image edges and often lead to segmentation failure when adopting Gaussian filter.

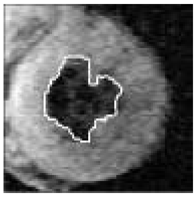
In order to validate the efficiency of this paper's algorithm which improve filter function and can realize adaptive segmentation, we take a heart's MRI image for example.



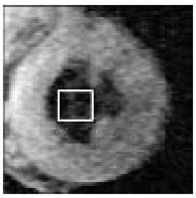
(a) The initial contour in external



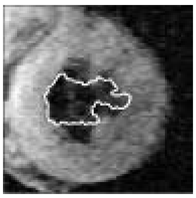
(b) Segmentation Result 1 of DRLSE



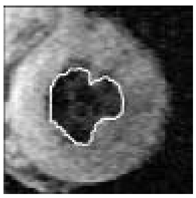
(c) Segmentation Result 1 of the improved algorithm



(d) The initial contour in internal



(e) Segmentation Result 2 of DRLSE



(f) Segmentation Result 2 of the improved algorithm

Fig.1 Segmentation Results

From Figure 1 and Table 1, we can see that the improved algorithm don't need defined constant evolution speed's symbol. It can realize adaptive evolution inwards or outwards according to the direction of the unit normal vector. However, DRLSE model need to define the constant evolution speed's symbol according to the position of initial contour. On the other hand, the improved algorithm adopting improved filter function protects the edge information, needs fewer iteration times and greatly reduces computational cost. The improved algorithm extracts the contour more accurately than DRLSE model.

Table 1 Data of Experiment 1

Model	The position of initial contour	Constant evolution speed	Iteration times	Cost times
DRLSE	external	1.5	300	41.1719s
Improved algorithm	external	1.5	150	33.1094s
DRLSE	internal	-1.5	700	84.1719s
Improved algorithm	internal	1.5	300	67.2031s

5. Conclusions

The algorithm in this peper has the ability of adaptive segmentation. Whatever the initial curve surrounds the target boundary or is inside the target boundary, the algorithm can all extract the object contour. Besides, it can extract contour of the medical image accurately which contains strong noise, and reduce requirement of human-computer interaction. We can apply the algorithm in this paper for computer auxiliary medical diagnosis, and to help doctors extract the nidus's contour.

Acknowledgment

Financial support for this project was obtained from Natural Science Foundation of Fujian Province (2010J01327), Fujian Provincial Key Laboratory of Photonics Technology and Fujian Education Department Technology Foundation (JB07040), which are greatly acknowledged, and great thanks to all colleagues who previously provided technical support.

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