A Level Set Segmentation Method of Medical Image Based on Region and Boundary

Zuojun Liu
1Faculty of Computer and Software Engineering, Huaiyin Institute of Technology, Huai'an, 223001, Jiangsu, China
hyliuzj@126.com

Lihong Li
2Faculty of Foreign Language, Huaiyin Institute of Technology, Huai'an, 223001, Jiangsu, China
hylilihong@126.com

***Abstract*—Aiming at the shortages of some segmentation methods of medical image, a novel level set segmentation method based on global information, local information and boundary information is proposed. The global information is described by C-V model, and the local information is described by information entropy model, and the boundary information is described by gradient model. The total energy description model consists of three models. Then, the total energy model is embedded into a level set. The extremum of the total energy function can be got by variation. The variation of the total energy just is the evolution equation of the curve. Because of the global information, the local information and the gradient information, the evolution equation can locate the boundary of the image accurately and segment the image accurately. Proved by experimentations, this method proposed in this paper can accurately segment medical images with uneven intensity and weak boundary.**

***Index Terms*—level set; medical image segmentation; C-V model; information entropy; gradient model; gradient descent flow**

I. Introduction

Precise segmentation of medical images plays an important role in clinical diagnosis, treatment, and postoperative monitoring. There are several reasons: (1) the medical image is fuzzy and uneven in intensity. (2) the medical image has local effects. (3) the medical images is uncertain. Among them, the level set method is one of the most popular methods. Level set method can be divided into two categories: the level set method based on the boundary[1] and the level set method based on the region[2].The level set method based on the boundary mainly depends on the image boundary information, which is sensitive to initialization and noises. The level set method based on the region depends on the intensity of the image. It is based on the hypothesis of luminance consistency. Chunming Li proposed the local binary fitting (LBF) model[3], which transformed the problem of image segmentation into searching optimal curve and its corresponding local binary fitting function. The LBF model has stronger local properties and can effectively segment the weak boundary targets. But the local properties can lead it to trap into local extremum. Liang Liming proposed a segmentation method based on Hessian matrix and level set[4], and used it to segment the retinal vessels. Hessian matrix method can be used to calculate the secondary partial derivative of 2d image. The secondary partial derivative of an image is just the Hessian matrix. Hessian matrix describes the local second order structure--curvature of an image. The different combination of the eigenvalue describes the shape of the image[5]. But the Hessian matrix will lead to misjudges when meet nodular structure. Snake Model proposed by M.Kass is also called the Active Contour Model (ACM)[6], which has been widely used in image segmentation. This method attribute the problem of image segmentation to minimizing the energy functional of a closed curve, which then can be used as the evolution function of level set, so as to approximate the contour of the target. There are many methods based on ACM[7,8]. Three main disadvantages of these models are as follow: (1) these models depend on the parameters of the curve, which is not intrinsic. (2) the models depend on the initial position of the curve. (3)these models cannot detect the sunk boundary of the image. Chan proposed a Chan-Vese model (C-V model)[9], which is also known as borderless active contour model. This model assumes that an image is composed of two parts: target and background. This method has many advantages: robust to noise, lower requirements to initialization, arbitrary initial contour, no depending on the boundary information. There are also some shortcomings: (1) it is too rough to descript image region with the average intensity. (2) no ideal results will be achieved when the regional mean and variance of the two categories are not similar at the same time. The C-V model assumes that the intensity of the region is even. But, the intensity of medical image is often uneven.

In this paper, a novel method is proposed based on the C-V model. The C-V model is used to describe the global information of image region. The local information is described by the information entropy, which can overcome the deficiencies of C–V model and accurately descript the local information of the image. In image segmentation, the boundary information of image is the most important.

Therefore, the image gradient is introduced in this paper to fully utilize the boundary information. On this basis, this paper constructs the total energy model, which is the evolution equation of the curve, to realize the segmentation of medical image. After repeated experiments, this method is proved to be very effective in segmenting medical images with uneven intensity and weak boundary.

II. SEGMENTATION MODEL

Aiming at the existing problems of medical image segmentation, a level set segmentation model is proposed, which integrates C-V model, information entropy model and gradient model.

A. Region segmentation model

The method of image segmentation based on region information groups the similar components with same intensity into one region. This method assumes that the same region has same property and different region has different property. How to extract the intensity information of image region is the key to region segmentation.

B. C-V Model

Assuming, a closed curve C segment the whole region of an image into internal region and external region. The intensity of internal region and external region reflects the differences of the target and the background. The closed curve C is just the active contour of the object. Based on this idea, Chan and Vese, based on Mumford-Shan function, proposed the active contour method. The energy functional of this model is shown as formula (1).

$$E^{CV} = \lambda_1 \int_{inside(C)} |I - c_1|^2 dx + \lambda_2 \int_{outside(C)} |I - c_2|^2 dx \quad (1)$$

In formula (1), λ_1 and λ_2 are non-negative. Inside(C) is the region in the image and outside(C) is the region out the image. c_1 is the average intensity inside curve C and c_2 is the average intensity outside curve C.

C-V model can effectively describe the global information of the image based on even intensity. It is difficult to segmentation image with uneven intensity. But, the intensity of medical image is just uneven. Therefore, the simple C-V model can only descript the global information of the image. The ability to descript the local information is insufficient for this model.

B. Information entropy model

According to information theory, information entropy is a measure of information. Following Shannon's definition about entropy, the information entropy of the image is shown as formula (2).

$$E(I) = -\sum_{i=1}^{N} P_i \log P_i \quad (2)$$

P_i is the probability of image I.

The information of image in different region is different. To descript the different region of the image, the information entropy should be calculated. The definition of certain region of the image is shown as
formula (3).

$$E^E(x, \Omega_x) = -\frac{1}{\log|\Omega_x|} \int_{\Omega_x} p(y, \Omega_x) \log P(y, \Omega_x) \quad (3)$$

$p(y, \Omega_x)$ is the distribution function of intensity, and its definition is shown as formula (4).

$$p(y, \Omega_x) = I(y) \int_{\Omega_x} I(z) dz \quad , y \in \Omega_x \quad (4)$$

The information entropy can effectively describe the local information of the image and can detect whether the intensity of a region is even. And it is robust to uneven image. The more even of the intensity is, the lower the information entropy is. The information entropy can effectively describe the change of image intensity. The introduction of the information entropy can overcome the deficiency of the C-V model.

C. CVE Energy model

The C-V model can describe the global information of the image, but it cannot describe the local information of the image. So, the simple C-V model is difficult to achieve the ideal segmentation effect. The information entropy can describe the local information of the image. Therefore, based on the C-V model, a method is proposed combining with information entropy model. The C-V model is used to describe the global information of the image, and the information entropy model is used to describe the local information. A model fusing both global information and local information is built, that is CVE model. The CVE model has the ability of C-V model to represent the global information and the ability of information entropy to represent the local information. The energy function of CVE model is shown as formula (5).

$$E^{CVE}(C, c_1, c_2) = (1 - \omega) E^{CV} + \omega E^E \quad (5)$$

The competition strategy is introduced between C-V model and the information entropy model. When $1 - \omega$ value is bigger, the C-V model plays a leading role. Otherwise, the information entropy model plays a leading role.

D. CVE Level set energy model

Embedding a level set in formula (5), the level set energy model is shown as formula (6).

$$E^{CVE}(\emptyset, c_1, c_2) = \sum_{i=1}^{2} \lambda_i \int_{\Omega} |I(x) - c_i(x)| M_i(\emptyset(x)) dx + \sum_{i=1}^{2} \lambda_i \int_{\Omega} E^P(x) M_i(\emptyset(x)) dx \quad (6)$$

In formula (6), $M_1(\emptyset) = H(\emptyset)$, $M_2(\emptyset) =$ 1-$H(\emptyset)$,
$H(\emptyset)$ is approximated by $H_\varepsilon(\emptyset)$, $H_\varepsilon(\emptyset)$ is shown as formula (7).

$$H_\varepsilon(\emptyset) = \frac{1}{2}\left(1 + \frac{2}{\pi} \arctan\left(\frac{x}{\varepsilon}\right)\right) \quad (7)$$

$\delta_\varepsilon(\emptyset) = \frac{1}{\pi} \frac{\varepsilon}{\varepsilon^2 + \emptyset^2}$ is the derivative of $H_\varepsilon(\emptyset)$.

An additional internal energy can be added into formula (6) to normalize the level set function to prevent over fitting. The additional internal energy is shown as formula (8).

$$P(\emptyset) = \int_{\Omega} \frac{1}{2} (|\nabla \emptyset(x) - 1|) dx \quad (8)$$

Another length penalty is added into the formula (6) to make the evolution curve smoother. The formula is shown as formula (9).

$$L(\emptyset) = \int_{\Omega} (|\nabla \emptyset(x)|) dx \quad (9)$$

After adding additional internal energy and length penalty under the level set framework, the energy model of formula (6) is modified as formula (10).

$$E^{CVE}(\emptyset, c_1, c_2) = \sum_{i=1}^{2} \lambda_i \int_\Omega |I(x) - c_i(x)| M_i(\emptyset(x))dx + \sum_{i=1}^{2} \lambda_i \int_\Omega E^P(x) M_i(\emptyset(x))dx + \mu \int_\Omega \frac{1}{2}(|\nabla\emptyset(x) - 1|)dx + \nu \int_\Omega (|\nabla\emptyset(x)|)dx \quad (10)$$

In formula (10), μ and ν is weighted positive constant, c_1 and c_2 are shown as formula (11).

$$c_1 = \frac{\int_\Omega I(x) H_\varepsilon(\emptyset(x))dx}{\int_\Omega H_\varepsilon(\emptyset(x))dx}$$

$$c_2 = \frac{\int_\Omega I(x)(1 - H_\varepsilon(\emptyset(x)))dx}{\int_\Omega (1 - H_\varepsilon(\emptyset(x)))dxdx} \quad (11)$$

E. Gradient level set energy model

The intensity of each part in the image is various. The intensity of each region in an image can effectively describe the region information. And the boundary of the image corresponds with the dramatic change of intensity. In mathematics, the changes of the intensity can be described by gradient. The boundaries can be found when the gradient reaches the local maximum. Gradient plays important role in image processing. Therefore, based on the local and global information, this paper introduces the gradient information to get more effect in medical image segmentation. The gradient energy model embedded into level set is shown as formula (12).

$$E^G = \int_\Omega g|\nabla H(\emptyset)|d\Omega \quad (12)$$

In formula(13), g is a boundary detection function to detect the boundary of images. The definition of g is shown as formula (13)

$$g = \frac{1}{1+\nu|\nabla I|^2} \quad (13)$$

F. A level set energy model based on region and boundary

Region information and boundary information are important in describing the image region. The energy functional model with region information and boundary gradient information is shown as formula (14).

$$E^{CVE}(\emptyset, c_1, c_2) = \sum_{i=1}^{2} \lambda_i \int_\Omega |I(x) - c_i(x)| M_i(\emptyset(x))dx + \sum_{i=1}^{2} \lambda_i \int_\Omega E^P(x) M_i(\emptyset(x))dx + \alpha \int_\Omega g|\nabla H(\emptyset)|d\Omega + \mu \int_\Omega \frac{1}{2}(|\nabla\emptyset(x) - 1|)dx + \nu \int_\Omega (|\nabla\emptyset(x)|)dx \quad (14)$$

In the formula(14), α, μ, ν are all non-negative constant to balance each item.

G. Gradient descent flow

The target of image segmentation is to search the boundary of an image. Fixed the level set function Φ, c_1 and c_2, the gradient descent flow can be got by minimize E^{CVEG}. The formula is shown as (15).

$$\frac{\partial\emptyset}{\partial t} = \delta_\varepsilon(\emptyset)(F_1 + F_2 + F_3) + \nu\delta_\varepsilon(\emptyset)\mathrm{div}\left(\frac{\nabla\emptyset}{|\emptyset|}\right) + \mu\left(\nabla^2\emptyset - \mathrm{div}\left(\frac{\nabla\emptyset}{|\emptyset|}\right)\right) \quad (15)$$

$F_1 = \omega(-\lambda_1(I(x) - c_1(x))^2 + \lambda_2(I(x) - c_2(x))^2$ is the global fitting item, $F_2 = (1-\omega)(-\lambda_1 \int_\Omega E^P(y)dy + \lambda_2 \int_\Omega E^P(y)dy)$ is the local fitting item, $F_3 = g\left(\frac{\nabla\emptyset}{|\emptyset|}\right)$ is the gradient fitting item.

H. Implementation

The formula (15) is just the curve evolution equation. The initial curve evolution equation is constantly approximating the boundary of the image until the convergence condition is satisfied. The steps of the algorithm are shown as follows:

(1)To initial the contour C_0 and level set function Φ.

(2) parameters setting: to set $\omega, \lambda_1, \lambda_2, \mu, \nu$ and so on.

(3) to calculate the global fitting item F_1, to calculate the local fitting item F_2, to calculate the gradient fitting item F_3.

(4) according to the curve evolutionary formula(15), to evolute the level set Φ.

(5)The algorithm will return to step(3) if the convergence condition is not satisfied. Otherwise, the algorithm will be ended.

III. EXPERIMENTAL VERIFICATION

In order to verify the performance and efficiency of the proposed method, lots of experiments were done respectively by the gradient method, C-V method, the method of literature[3] and CVEG method under the same conditions. All these methods are simulated with MATLAB2016a. The CPU is Pentium 1.8 G. The memory is 4GB RAM. The operating system is Windows7. The parameters in the experiment are shown as following: C_0=3, Δt=0.05, $\lambda_1=\lambda_2$=1, μ=1, α=1, σ=2, ν=0.02*255*255, $\omega = 0.98$. The values of each parameter are the optimal value proved by lots of experiments.

Gradient method need not to be iterated. The times of iteration of C-V model, literature[3] and CVEG are selected through experiments, which can achieve the best segmentation results.

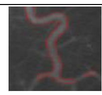
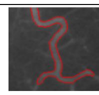
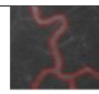
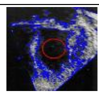
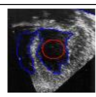
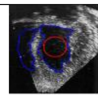
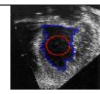
In order to verify the performance and efficiency of these methods, three kinds of images: composite image, medical blood vessel image and complex medical image are selected. The medical images used in the experiments were taken from two public databases: Caltech101 and Caltech256. In order to illustrate the comparison effect, the segmentation results of three types of images are listed in table 1. The size of the input image is preprocessed to 128* 128.The selected images are all lower signal-to-noise ratio.

The first image contains only simple shapes, which is a composite image to compare the universality of the four methods. To verify the structure performance of the four methods, the second image is a medical vascular image with medical structure, lots of noises and blur boundary. The third image is a medical image with complex structure and all kinds of noise to compare the performance and efficiency of four methods.

A. Performance comparison

The segmentation results of gradient method, C-V method, literature [3] and CVEG method are shown in table 1.

Table 1
the experiment results

	Gradient	C-V	Literature[3]	CVEG
image1				
image2				
image3				

To the first image, all of the four methods can achieve very good results, but the gradient method is the simplest. The gradient method can achieve similar results with other three methods, mainly because the gradient method can detect effectively the boundary of the image. In this paper, the gradient information of image is introduced, which can be used to detect the boundary of image, especially the blurring boundary.

As to the second image, the gradient method gets a poor effect, which indicates that it is especially sensitive to noises. The method of C-V and literature [3] can achieve better effect. But they are still insufficient in detecting the blur boundary of the blood vessels. The CVEG method can accurately separate the complete contour of the vessel even if the image is very fuzzy on the boundary.

For the third image, the gradient method is very poor for the noises. The C-V method and literature[3] can achieve a better effect. But, both the two methods have shown some error segmentation. The CVEG method can accurately get the complete contour of the image and without error segmentation.

It can be seen from these experiments, the CVEG method proposed in this paper is perfect with higher segmentation accuracy, lower error segmentation and strong robustness.

B. Time comparison

The times of the four methods are shown in table 2.

Table 2
Times and Time comparison (second)

	Gradient		C-V		literature[3]		CVEG	
	ts	t	ts	t	ts	t	ts	t
image1	0	0.8	120	8	120	16	120	15
iamge2	0	3.1	220	19	220	23	220	27
image3	0	3.5	410	41	410	52	410	57

In the table, ts means the times of iteration, and t means the time cost. As can be seen from table 2, the gradient method is the fastest for no iterations. The CVEG method cost a little more time compared with C-V method and literature[3]. But, the performance and effect is the best.

C. Comprehensive analysis

Seen from the analysis on table 1 and table 2, the gradient method is the fastest, but the effect is too far from the requirements of all kinds of applications. The C-V method and literature [3] cost a little shorter time compared with CVEG method, but there are some error segmentations and the effect is not ideal. The CVEG method proposed in this paper shows the best accuracy, performance and strong robustness which can meet the requirements of practical applications. This method is universal to some extent, which can be used to segment many kinds of images.

CONCLUSIONS

A novel level set method based on region and boundary is proposed in this paper. This method introduces the global intensity fitting item, the local intensity fitting item and the gradient fitting item, which can segment image with uneven intensity and blur boundary. The effect and performance is perfect. The method is strong robust.

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