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A Fast and Robust Segmentation method for Liver Tumor

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Abstract
To segment the liver tumor accurately, this paper proposes a segmentation method which combines relative fuzzy connectedness with level set method. First, liver tumor is roughly segmented using relative fuzzy connectedness. Second, the result of preliminary segmentation is as the initial contour of level set method. The accurate boundaries of liver tumor are then segmented using level set method. Last, an adaptive velocity evolution function is

designed to accelerate the evolution rate of the curve. The experiment results show that this method is robust to the placement of initial curve, needs a smaller number of iterations to achieve convergence, and the tumor edge segmented is more close to the result segmented manually by doctors compared with classical CV model.

Keywords: ADAPTIVE VELOCITY EVOLUTION FUNCTION, LEVEL SET, MEDICAL IMAGE SEGMENTATION, LIVER TUMOR, FUZZY CONNECTEDNESS

1. Introduction

Liver is one of the most important organs in the body of human beings. With the deterioration of the natural environment and the increase of stress in life in recent decades, the occurrence of malignant liver tumor (liver cancer) becomes more common and serious. In 1990, liver cancer was the fourth cancer killer in the world. While in 2000, it turned into the third one. Each year over one million new cases emerged and about 260,000 patients died of liver cancer [1]. The situation is more serious in our country. Since the 1990s, liver cancer has been the second cancer killer in China [2]. The incidence of liver cancer is higher than the global average. The occurrence of liver cancer has a strong concealment. At the early stage of liver cancer, patients neither have special symptoms nor have similar signs as tumor patients, so they are not aware of the disease. However, once the cancer symptoms appear, the disease is already at the middle stage or even the late stage. At this time, surgical treatment is the most effective way to treat liver cancer.

In recent years, with the development of the quality of medical equipment (CT, MRI, PET, etc.), the quality of medical images has been improved increasingly. So medical image plays a growing role in clinical application and can increase the accuracy of diagnosis of all kinds of diseases. Medical images could provide doctors more accurate pathological information of organs. The researches in medical images processing mainly focus on the enhancement, segmentation, blending of images and three-dimensional visualization. Image segmentation is actually a procedure of region subdivision. According to consistency principle, each generated region has unique properties different from other regions. Medical image segmentation is the key procedure of extracting interested regions of patients and the necessary premise of deep analysis of images information. In general, medical image segmentation methods can be divided into five main categories: 1) pattern recognition-based methods [3]; 2) active contour model-based methods [4]; 3) tracking-based methods [5]; 4) artificial intelligence-based methods [6]. 5) neural network-based methods [7]. The active contour model-based methods are most used in medical image segmentation, which could be divided into two subcategories based on the type of curve evolution: 1) parametric active contour model-based methods [8]; 2) geometric active contour model-based methods [9]. Parametric active contour model-based methods utilize parametric equations to explicitly represent evolving curves, in which the snake model is the most classical method [8]. In the snake model method, the curve is deformed as a result of the influence of local forces derived from edge points, while this deformation remains smooth due to the effect of internal forces. The snake model has two drawbacks: one is highly sensitive to the parameterization of the curve and another is that the explicit representation of the curves prohibits any topological changes during evolution. Geometric models for active contours are based on the theory of curve evolution geometric flows. These models are usually implemented using numerical algorithm based on level set. The level set method (LSM) is a numerical technique for tracking interfaces and shapes. Osher proposed a method to set up the level set model based on the Hamilton-Jacobi equation [9]. Malladi et al. applied the level set function to image segmentation[10]. Chan and Vese proposed a CV model based on regional information, which drove the evolving curve by minimizing the fitting error and simplifying the Mumford–Shah model [11]. This method is robust against noise by utilizing the regional image features, and it has been successively extended in different ways. However, these methods don't periodically solve a PDE (partial differential equation) to keep the level set function to be a signed distance function. This process has a large amount of calculation. Li et al. introduced a variational level set method to eliminate reinitialization by incorporating a penalizing term into the energy functional used in the geodesic active contour model [12]. Due to the advantage of CV model and variational level set method, a large amount of improved algorithms was proposed which achieved good results in their respective application fields [13-17].

Although the geometric active contours models can work well on many segmentation problems, they still have certain limitations when applied on liver tumor segmentation. The major problem is the initial placement of the contour. If initial contour is not accurate, it may lead to wrong segmentation and low reliability. Additionally, this method needs a large number of iterations and calculation. To segment the liver tumor area of liver accurately and fast, this paper proposes a segmentation method which combines relative fuzzy connectedness with level set. First, liver tumor is initially segmented by relative fuzzy connectedness [18]. The result of preliminary segmentation is as the initial contour of level set method. Then the accurate boundaries of liver tumor are segmented by level set method. Finally, an adaptive velocity evolution function is designed to accelerate the evolution rate of the curve. The experiment results show that the method proposed in this paper needs a smaller number of iterations to achieve convergence, and the tumor edge segmented is more close to the result segmented manually by doctors compared with classical CV method.

2. Methodology

2.1. Geometric Active Contour

Geometric active contour model was proposed by Osher and Sethian, and implicitly represents the deformable contour in a level set framework [9]. The deformable contour can be represented as shown in Eq. (1)

$$C(t) = \{(x, y) \mid \phi(x,t) = 0\} \tag{1}$$

$\phi(x,t)$ is a signed distance function, also called as a level set function and can be written as Eq. (2)

$$\phi_t + F\,|\nabla\phi| = 0 \tag{2}$$

where F represents the velocity of the evolution. The stop criterion $g(x)$ proposed by Malladi is a monotonically decreasing function based on the gradient magnitude of an image [10], as shown in Eq. (3).

$$g(x) = 1/(1 + |\nabla G_\sigma(x) * I(x)|^2) \tag{3}$$

The level set function $\phi(x,t)$ will stop evolving and finish segmentation when g approaches zero.

When the level set method is applied into liver tumor segmentation, there are still some drawbacks. The placement of the initial contour is a major problem. The liver tumor in medical images always possess so ambiguous margin like a discontinuity in boundaries, that it easily induces contour leaking. Another drawback is that the level set method often needs a large amount of iterations to finish segmentation and consumes a long time. So we use the segmentation of fuzzy connectedness as the initial contour of level set model.

2.2. An interactive and fast segmentation algorithm for image series

To obtain a good placement of initial contour for the level set method, the fuzzy connectedness method is utilized to extract the boundary of liver tumor from medical images [19]. First, some objective seeds region So and background seeds S1 should be chosen in an interactive way before the segmentation procedure by users. Then, for each voxel p in the volume dataset, the fuzzy connectedness of Sb and So should be computed respectively, and the relationship of voxel p is calculated according to Eq. (4),

$$R(p) = \mu(p, S_0) / \mu(p, S_0) \tag{4}$$

where $\mu(p,S_0)$ represents the local fuzzy connectedness between p and S0 in medical images and $\mu(p,S_1)$ represents the local fuzzy connectedness between p and S1 in medical images. When R > 1, the point p belongs to objective region, and when R ≤ 1, the point p belongs to background region.

A segmentation method for image series is obtained by applying the above algorithm into 3D image space. As shown in Figure 1, any voxel has a m-connectedness with neighboring voxels in 3D image space (m =6 or 26). White points represent center voxels, and black points represent the voxels connected with center voxels. This paper uses m = 6 connectedness.

The interactive segmentation algorithm based on relative fuzzy connectedness for image series can be mainly divided into the following steps:

Step 1: Open an image series, select an objective region and a background region by user, and initialize all the parameters.

Step 2: The fuzzy connectedness of the point p is calculated, and whether the point p belong to the objective region or the background region is determined according to Eq. (4)

Step 3: The segmentation of liver tumor is generated. The result will be as the initial contour of level set model.

This method just performs some simple options on a few images, without touching the most images, and can rapidly generate a reliable result of segmentation on image series.

2.3. Adaptive velocity evolution function

To achieve automatic selection of the curve evolution direction, only considering the local information of image is not enough. Reference [4] realized the nonlinear evolution speed and automatic selection of the curve evolution direction using the image region information. The evolving curve divides the image into two parts, as shown in Eq. (5).

$$A = A_1 + A_2 \tag{5}$$

A_1 represents the objective region, and A_2 represents the background region. Thus, the direction function is shown as follows:

$$direction(x, y) = P(A_1|I(x,y)) - Th \tag{6}$$

where Th is a constant threshold, and $P(A_1|I(x,y))$ is a posterior probability of pixels belonging to the object region. When $P>Th$, the pixel belongs to the object, $direction(x, y)$ is positive and the closed curve should expand to include the pixel. When $P<Th$, the pixel belongs to the background, $direction(x, y)$ is negative and the closed curve should shrink to exclude pixel. So the method achieves automatic selection of the curve evolution direction based on the image region information.

To further accelerate the speed of curve evolution, we develop an adaptive direction function based on Eq. (7)

$$v(x,y) = k[(1+\exp(-\zeta(direction(x,y))))^{-1} - 0.5] \tag{7}$$

where k is a constant parameter which controls the amplitude of evolution velocity, and ζ is a constant parameter which controls the nonlinear degree of the velocity. Eq. (7) is a sigmoid function. When P is close to Th, the pixels neither belong to the objective region nor background region, but on the boundaries. Then v takes a small value to avoid boundary leakage. On the contrary v takes a big value to accelerate the evolution of curve. In this way, the number of iterations is reduced and the segmentation process is accelerated.

3. Results and Discussion

To verify the precision and effectiveness of the method proposed in this paper, two groups of testing experiments are designed. The first experiment processes an error analysis and the other experiment processes an effectiveness analysis. Those experiments compare the proposed method with the CV model. In this paper, the experimental platform is shown as follow: CPU is Intel I7 2.5GHz, memory is DDR5 16.0GB, GPU is NVIDIA GeForce GTX860 and the size of GPU memory is 4G. Programming environment is Visual Studio C++.NET 2012.

The experimental datasets include four liver tumor image series. As Shown in Figure1, image (a), (b), (c), and (d) are original images in four image series respectively. The resolutions and slice number of four image series present in Table 1. Image series (a) and image series (b) are CT images with high contrast. Image series (c) and image series (d) are CT images with low contrast.

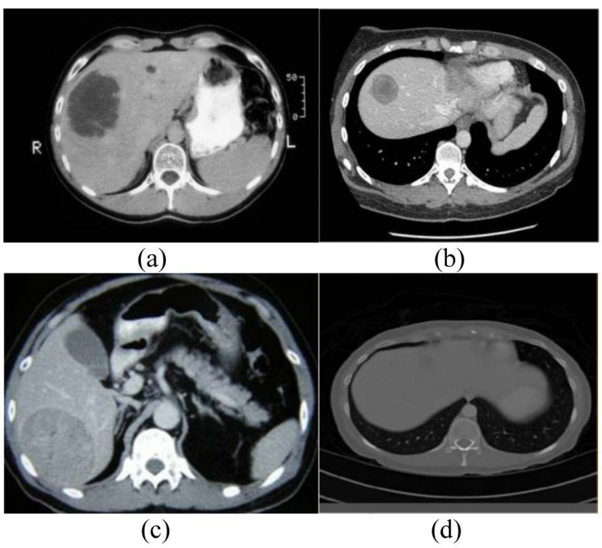

Figure 1. Image (a), (b), (c), and (d) are original images in four image series respectively

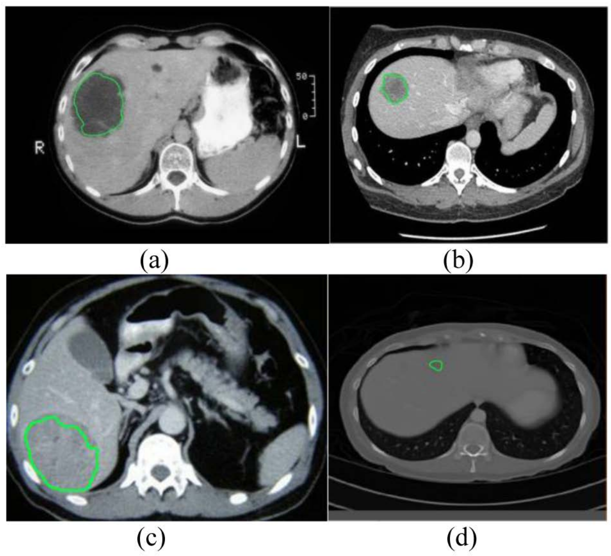

Figure 2. Segmentation results of liver tumor region using relative fuzzy connectedness

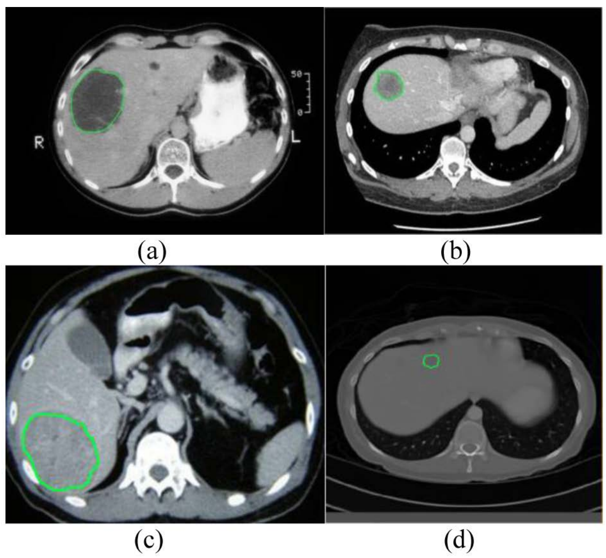

Figure 3. Segmentation results of liver tumor region in four image series using CV model

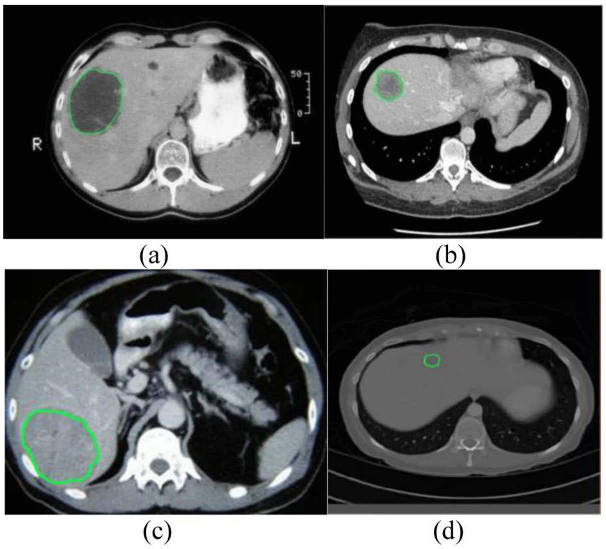

Figure 4. Segmentation results of liver tumor region in four image series using the method proposed in this paper

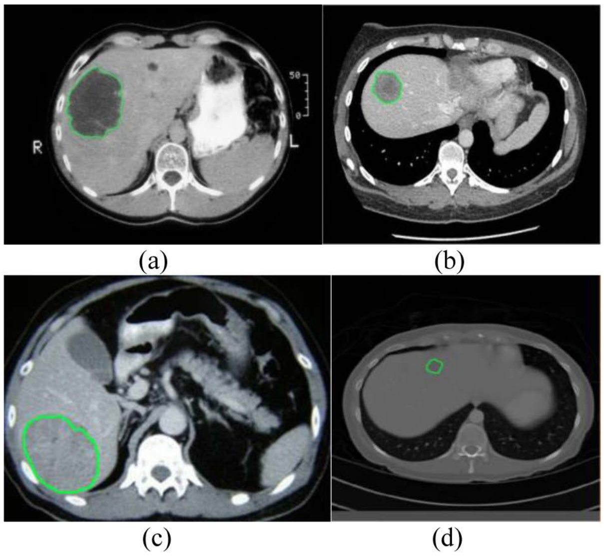

Figure 5. Referenced segmentation results of liver tumor in four image series

In Figure 1, row (a) are original images in four image series respectively, row (b) are images segmented by relative fuzzy connectedness, row (c) are images segmented by CV model, row (d) are images segmented by the method proposed by this paper, and row (e) are standard images segmented by doctor manually.

The error ratio e is computed using Eq. (8)

$$e = (E_1+E_2)/S \quad (8)$$

where E_1 is the sum of pixels which belong to non-tumor region but are classified into tumor region, E_2 is the sum of pixels which should belong to tumor region but are classified into non-tumor region, and S is the sum of pixels of real tumor region. The reference images are segmented by doctor manually.

Table 1. The four datasets of experiment

Image Series	Resolution	Image Slice Numbers
a	512×512	86
b	512×512	94
c	512×512	88
d	512×512	102

Table 2. The Error ratio of the methods: Fuzzy connectedness, CV model, and the proposed method

Image Series	Fuzzy Connectedness	CV Model	The Proposed Method
1	12.4%	5.1%	4.2%
2	11.5%	4.8%	4.4%
3	17.1%	12.8%	8.3%
4	28.6%	18.4%	12.2%

As shown in Table 2, for the dataset 1 and 2 with high contrast, the segmentation results by CV model are close to the results by the method proposed in this paper, and the average error ratio of the proposed method is 13.13% less than that of CV model. While for the dataset 3 and 4 with low contrast, the performance of the method proposed in this paper is much better than CV model. The average error ratio of the proposed method is 34.29% less than that of CV model. The experimental results show that the method proposed in this paper can obtain a good segmentation result when applied on the datasets with a low contrast. The execution time is compared between the proposed method and CV model in Table 3. As shown in Table 3, the average execution time of the proposed method is 25.4% less than that of CV model. So the proposed method can obtain a higher efficiency.

Table 3. The execution time of the methods: Fuzzy connectedness, CV model, and the proposed method

Image Series	Fuzzy Connectedness	CV Model	The Proposed Method
1	1.8s	15.5s	10.7s
2	1.8s	16.5s	10.9s
3	1.9s	18.8s	11.4s
4	1.9s	19.6s	12.1s

Conclusions

To obtain a precise segmentation of liver tumor, this paper proposes a segmentation method combining relative fuzzy connectedness with level set. First, liver tumor is preliminary segmented by relative fuzzy connectedness. The results of segmentation are then as the initial contours of level set method. Second, the accurate boundaries of liver tumor are segmented by level set method. Last, an adaptive velocity evolution function is designed to accelerate the evolution rate of the curve. The experiment results show that this proposed method can accelerate the speed of processing and improve the precision of segmentation.

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