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Segmentation of Medical Serial Images Based on K-means and GVF Model

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Abstract: The medical CT images are irregular and have deep boundary concavities. So how to get the organ picture from serial images quickly and accurately is a difficult process. The paper discusses the shortcoming of GVF model being susceptible to structures with slender topology. For the better convergence we improve GVF model by setting the initial contour as the actual contour. The new algorithm combines k-means cluster with GVF model. Firstly, the target organ is extracted from a CT slice through k-means cluster and morphological reconstruction, and then its edge is set as an initial contour of the adjacent CT sequence, finally, the organ is segmented from a sequence of images with GVF algorithm. The process is repeated until all slices from entire CT sequences are obtained. The new algorithm has higher segmentation accuracy and lower complexity.

Keywords: K-means, GVF, initial contour.

1. INTRODUCTION

In order to diagnose disease correctly, we need to extract organ region from the medical images sequence accurately and quickly [1]. However, the organ usually has complex structures. Firstly, the CT image includes many organs like liver, spleen, kidney, and so on. Threshold method is difficult to distinguish the organs for their grey values are similar. Secondly, the edge of organ in CT image is often ambiguous. So it is difficult to segment with edge-based segmentation method. Lastly, shapes of organs have differences for individuals. Even for the same person, organ shapes at different times are not the same [2]. For such reasons above, there are a lot of problems to segment organ exactly from CT images. At the same time, a set of CT serial images has hundreds of pieces, and the algorithm cannot be applied if it costs too much time.

The GVF model is commonly used to find the contour of an organ in a medical image. It can get a good result with low-level information and high-level knowledge of image [3, 4]. But it needs a given initial contour when segmenting object. Artificial contour initialization is complicated and wastes time. The result of segmentation is influenced by manual initialization on a large extent [5]. It is seen that initial contour in GVF snake model is very important. The GVF model can get a correct contour only when setting the initial contour inside the "effective area". Therefore, how to initialize contour is the key to the GVF Snake model.

2. K-MEANS CLUSTER TO DETERMINE THE INITIAL CONTOUR

We determine the initial contour using k-means cluster and morphological reconstruction.

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2.1. k-means Cluster

The central idea of k-means clustering is to minimize distance within the class, and the sample data will be divided into k classes scheduled.

For cluster, suppose (x, y) as pixel coordinate of image, then g (x, y) represents grey value of the pixel. The pixel data is divided into k classes, where j represents the category number and, $c_j^{(i)}$. represents the j-th iteration of the set of pixels of the j class, $u_j^{(i)}$. is the grey mean of pixels in the j-th class set after i iterations [4].

The Substantive issue of k-means cluster is to find a partition C={C1,C2,…,Ck}. The partition can get a minimum distance E within the class by calculation of formula 1.

$$E = \sum_{j=1}^{k} \sum_{(x,y)\in C_j} ||g(x,y) - u_j||^2 \tag{1}$$

The specific algorithm is described below:

(1) Determine the initial mean:

Select the centroid points of the k-th cluster randomly, and their grey values are shown as, $u_1^{(1)}, u_2^{(1)}, ...u_k^{(1)}$

(2) Grouping:

Formula 2 can calculate which pixel belongs to which class according to the distance from the mean of each class. Then pixels are divided into the class in accordance with the minimum distance.

$$C_j^{(i)} = \operatorname{argmin}_{j=1}^{k} ||g(x,y) - u_j^{(i)}||^2 \tag{2}$$

If the distance between the grey value of the pixel and the mean of the j class is the shortest, the pixel belongs to class j and is contributed to, $c_j^{(i)}$.

(3) Re-calculate the class mean:

For each class j, is recalculated the average grey value of pixels in the class by Formula 3.

$$u_j^{(i+1)} = \frac{1}{N_j}\sum_{(x,y)\in C_j^{(i)}} g(x,y) \quad (3)$$

Where in, ,N_j. is the number of pixels in, $c_j^{(i)}$.

(4) For each j (j = 1,2, ..., k),if the equation , $u_j^{(i+1)} \approx u_j^{(i)}$. exists, the algorithm ends. Otherwise, step (2) and step (3) are repeated until convergence [5].

Through k-means algorithm, we can get organs segment more acutely from medical images, and can use the segment edge as the initial contour.

2.2. Morphological Reconstruction

The image after clustering is composed of discrete points. There are many clutter points and noise points in addition to liver region. The method to remove noise points directly by corrosion will affect the accuracy of the liver edge.

Therefore, we separate liver from CT image using morphological reconstruction method after clustering. The morphological reconstruction involves two images and a structural element, one is a marked image which contains the starting point of the transformation, and the other is a template image which defines the transformation.

The core algorithm of Morphological reconstruction is geodesic dilation and geodesic corrosion. We use morphological dilation to process image, let F be the tagged image, G as template image, and F ⊆ G, then: the definition of geodesic dilation is given as Eq. (4):

$$D_G^{(1)}(F) = (FB) \cap G \quad (4)$$

The morphological reconstruction of the template image of G using the marked image F is represented as Eq. (5):

$$R_G^D(F) = D_G^{(k)} \quad (5)$$

The image iterates k times until it reaches a steady state as shown in Eq. (6). [6]

$$D_G^{(k)}(F) = D_G^{(k+1)}(F) \quad (6)$$

3. GVF MODEL

Active contour model is also known as "Snake" model because in the process of approaching the target contour, the closed curve changes its shape like a snake. In recent years, active contour model is commonly used in medical image segmentation. It may converge to the irregular edge of the organ.

Snake model makes the parameterize curve to "energy minimization" so that the initial contour may get close to the boundary of the object little by little. Energies are divided into internal energy, external energy and image energy.

The contour curve is represented by formula V (s) = (x (s), y (s)), s ∈ [0,1], where s is the Fourier descriptor of the contour. The energy curve expression of the image is given in Eq. (7):

$$E_{snake} = \int_0^1 E_{int}(\upsilon(s)) + E_{ext}(\upsilon(s))ds \quad (7)$$

The external energy E_{ext} is determined by the actual situation. Generally, the gradient size represents the external force of image. Its direction is opposite to the direction of the gradient vector.

Eq. (8) can satisfy the minimum of energy E_{ext}.

$$E_{int} + E_{ext} = 0 \quad (8)$$

Due to structure complexity and shape variability of tissue, existing image segmentation methods are difficult to obtain the perfect results only depending on low-level visual attributes such as grey scale and texture properties. Therefore, it is urgent to get a flexible framework for medicine image segment. The framework can integrate information based on low-level visual attributes and the knowledge of the target to be split, such as a description of the target shape, brightness, color, doctor's experience, and then the complete expression of segmented region can be obtained.

Recently, GVF model has been commonly used in medical image segmentation. GVF model is based on the traditional snake model with static external force field V, thus expanding the scope of the force field, the model can converge to concave areas of object. F (x, y) is an edge gradient image, and the gradient vector field V (x, y) = (u(x, y,), v (x, y)).

The GVF model satisfies Eq. (9):

$$E = \iint u\left(u_x^2 + u_y^2 + v_x^2 + v_y^2\right) + |\nabla f|^2 |v - \nabla f|^2 dxdy \quad (9)$$

Seen by the calculus of variations, the gradient vector flow field satisfies the Euler equation Eq. (10):

$$\begin{cases} u\nabla^2 u - (u - f_x)(f_x^2 + f_y^2) = 0 \\ u\nabla^2 v - (v - f_y)(f_x^2 + f_y^2) = 0 \end{cases} \quad (10)$$

The Snake model is not feasible to get boundary concavities like "U" object, but the GVF model can solve the problem. However, if the initial contour is far from the actual contour, more number of iterations and larger amount of computation are needed. Furthermore, it will likely converge to the wrong result for narrow and deep concave region, and the algorithm is easy to fall into local extremes [6, 7].

The traditional active contour model cannot converge to the U-shape object, as shown in Fig. (**1**) GVF model can solve this problem, and it can converge to the real contour, as shown in Fig. (**2**). But for the narrow deep "U" object like Fig. (**3**) appears, the convergence cannot be accurately. Fig. (**4**) shows that initial contour set near the actual outline can make good convergence, and only costs less time of iterations.

Medical applications often need processing of hundreds of images. Each image segmented with GVF algorithm will spend too much time and cannot converge to boundary concavities. So GVF model is not directly used in CT image sequences which have complex structure. Setting initial con-

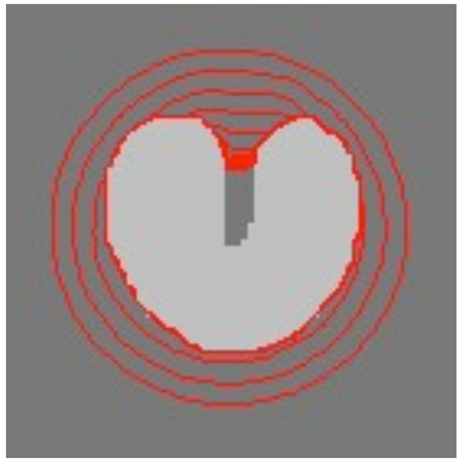

Fig. (1). traditional ASM for U-shape object.

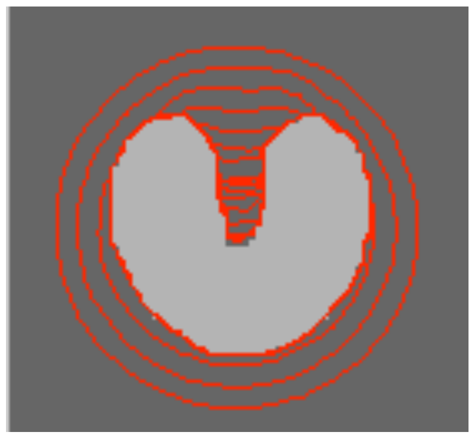

Fig. (2). GVF for U-shape object.

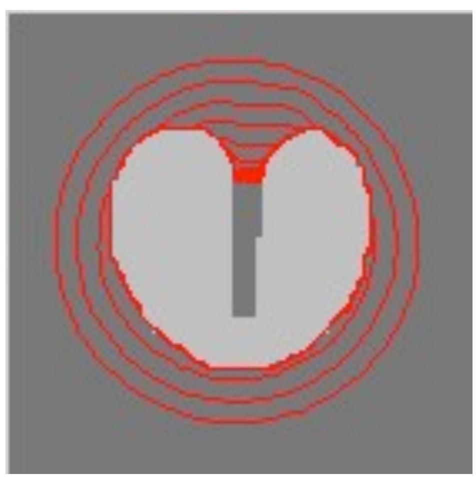

Fig. (3). GVF for deep U-shape object

tour by using manual methods will increase complexity for doctors. However, methods to obtain the initial contour like edge detection, threshold segmentation, wavelet method and so on cannot get closed edge except for interpolation [7]. In this paper, use k-means and morphological reconstruction for closed boundary curves as initial contour of GVF model and get the true contours in adjacent CT sequence pictures by GVF. Adjacent CT slices have smaller difference. Therefore, it can get real contour after less iteration.

4. EXPERIENCE

4.1. Experiment Results

In the experiments, serial images forming 64-slice spiral CT, were obtained from Zhu Jiang Hospital affiliated with Southern Medical University. The images contain several patients' abdominal CT sequences.

Fig. (4). GVF for deep U-shape object setting initial outline near real contour

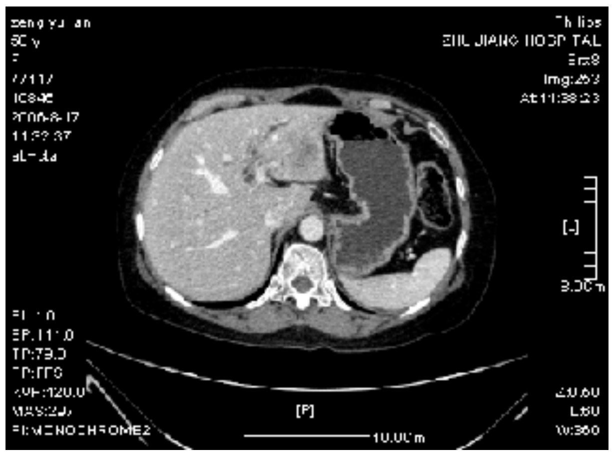

Fig. (5). original image.

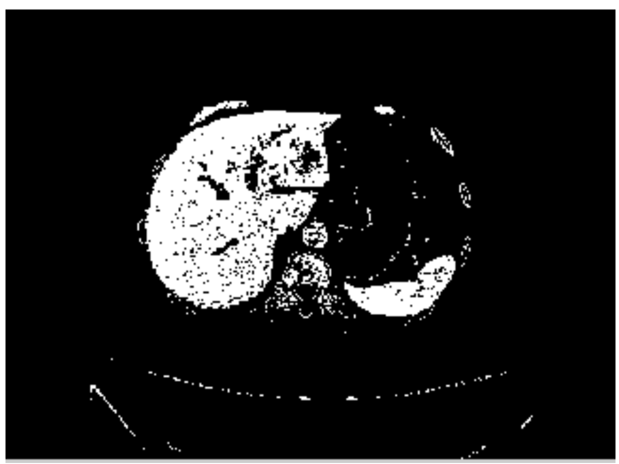

Fig. (6). k-means cluster.

As shown in Fig. (**5**), it is the 200 frame image in abdominal CT sequences. The frame has deep U-shaped region and fuzzy boundaries. We use improved k-means cluster to segment the original image, as shown in Fig. (**6**). Then use morphological reconstruction to improve image, as shown in Fig. (**7**). The segmentation result of the liver is very good, having smooth edge, especially the delicate part of the liver tip, as shown in Fig. (**8**).

Two adjacent CT images processed with GVF model can be obtained more on satisfactory edge. The processing results of the 100 frame and the 300 frame in serial images have been shown in Fig. (**9**) and Fig. (**10**) respectively.

4.2. Algorithm Speed

CT image sequences often have hundreds of images therefore, the speed of segmentation is very important. It is important to consider accuracy and efficiency in Algorithm design.

We made a comparison between the algorithms and conventional algorithms under the following condition.

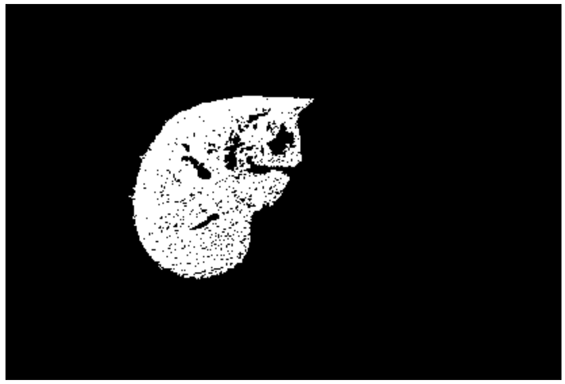

Fig. (7). morphological reconstruction.

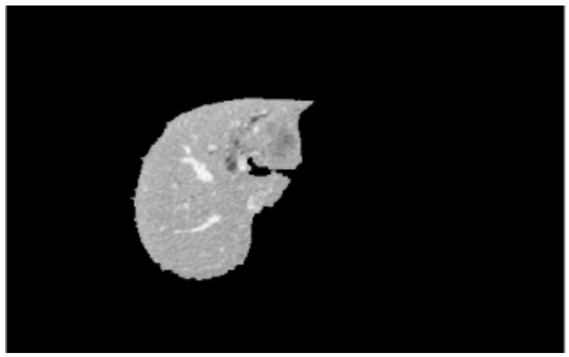

Fig. (8). segmentation result.

Fig. (9). liver segmentation of 100 frame image.

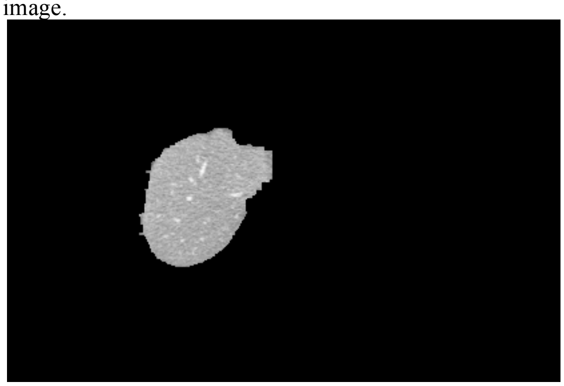

Fig. (10). liver segmentation of 300 frame image.

CPU: Intel Pentium(R) 4 CPU 3.06GHz

Memory: 2GHz

Operating environment: Matlab2010a

Under the same configuration and environment, the time-consuming of three methods is shown in Table **1**.

The watershed method consumes much time, but for complex image, the result of segmentation is not well; The GVF model can get similar effect with the method proposed in this paper, but costs more time. CT sequences often have hundreds of pictures, so time consuming must be considered. If the processing is too slow, it is difficult to apply to actual

Table 1. Running Time

Watershed	GVF	*This Algorithm*
2500s	1500s	150s

operation. The proposed algorithm can split liver more precise, cost less time and give more appropriate result.

5. CONCLUSIONS

The new algorithm uses k-means and morphological reconstruction algorithm to improve the initial contour of GVF model. The new algorithm can make the segment result more accurately and has faster speed. It can be well applied to the CT image sequences. Experiments show that the segment results provide a basis for the three-dimensional reconstruction and cancer recognition. Our next work is tumor detection and measurement.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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