JOURNAL OF PURE AND APPLIED MICROBIOLOGY, April 2013. Vol. **7**(Spl. Edn.), p. 453-459

Semi-Automatic Medical Image Segmentation Based on Improved Grow-Cut Algorithm

Huiyan Jiang*, Zhiyuan Ma and Mao Zong

Software College, Northeastern University, Shenyang - 110 819, China.

(Received: 03 March 2013; accepted: 14 April 2013)

Aiming at the segmentation of liver region in the abdomen CT image, we propose a novel method based on Grow-Cut algorithm. The Grow-Cut is an iterative algorithm, as the automation labels the image, user can observe the segmentation evolution and guide the algorithm with human input where the segmentation is difficult to compute. In this paper, we propose a new energy function for the traditional Grow-Cut method to obtain the better segmentation precision. Moreover, we do a pretreatment using the k-means to decrease the running time. In additions, we take multi labels for the Grow-Cut to get multiple organ segmentation results in one operation. Lastly, we take several experiments to demonstrate the validation of our proposed algorithm, and experimental results show that our method has a good robustness.

Keywords: Image segmentation, Graph Cut, Foreground Extraction, Cellular Automata, Multi-region Segmentation, K-means Optimization.

With the rapid development of modern medical technology, digital medical image has been widely used in disease diagnosis for clinical doctors and experts. The accurate segmentation of diverse tissues in the CT image is an integral part of not only a necessary premise before extracting features of diseases, but also a basic of the image three-dimensional reconstruction and the medical image visualization.

Human anatomy of different individuals is distinct, and the accuracy and time of the medical image segmentation approach are highly demanded by the clinical application. Image segmentation algorithm can be classified into two kinds, fully automated segmentation method and semi segmentation method. Fully automated algorithm like the threshold-based method(Sahoo *et al*, 1998; Sahoo *et al*., 1997), edge-based method(Basak *et al*, 1994), clustering method(Rezaee *et al*., 2000; Chen *et al*., 1998), region-based method(Chang *et al*. 1994; Cohen *et al*. 1987), and (Markov Random Field)-based method(Cross *et al*.,1983; Geman *et al*., 1983; Rick *et al*., 2009), Level Set method(Lin *et al*., 1997), etc. have been improved constantly. However no automated algorithm can be applied to any kinds of image with perfect result. For this reason, there are massive improved semi automated methods[1] proposed in research literatures, such as Boykov and Jolly (Boykov *et al*., 2001) proposed an interactive image segmentation based on graph cut, the random walker technique proposed by Grady and Funkalea(Grady *et al*., 2004), Intelligent paint(Reese, 1999) is a region based interactive segmentation method, which coordinates human-computer interaction to extract regions of complex backgrounds by paint strokes with a mouse.

Grow-Cut(Vezhnevets *et al*., 2005) is an interactive segmentation algorithm, which uses cellular automaton as an image model. Each cell of

* To whom all correspondence should be addressed.
E-mail: hyjiang@mail.neu.edu.cn

the automata has some label (in case of binary segmentation - 'object', 'background' and 'empty'). During automata evolution some cells capture their neighbors, and replace their labels. The Grow-Cut algorithm can accurately segment fuzzy regions by the aids of the anatomy knowledge and clinical experience of experts and doctors. Besides, the Grow-Cut algorithm can meet the commands of real process with its characteristics of fast speed and simple principle.

Based on the above analysis, we focus on the need to improve to Grow-Cut method. We proposed a novel monotonous decreasing function used for the automata evolution, and we adopt the k means algorithm to speed up the initial split speed. Lastly, we extend our algorithm to segmentation multi-region image, which owns more than one interested regions. We take several experiments to demonstrate our algorithm, and results have shown that our work has obviously improved the conventional Grow-Cut method. The outline of the proposed algorithm is shown as Figure 1.

The rest of the paper is organized as follows: In the next section, a fully describe of the related algorithm is introduced, including the cellular automata approach and the K-means algorithm. The proposed improved algorithm is described in section III. In section IV the validity of the proposed algorithm compared with other methods is given. Some conclusions are given in the last section.

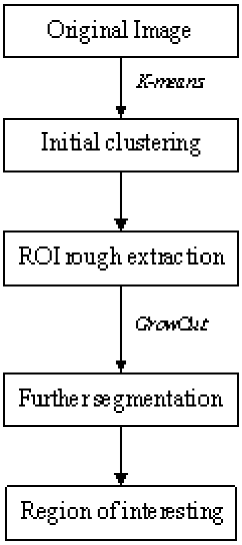


Fig. 1. The outline of the proposed algorithm

Related algorithm

Cellular Automata

Cellular automata (CA) algorithm (Neumann, 1966) was introduced by Von Neumann, which has been widely used in image de-nosing and edge detection. CA is a discrete dynamic system in time-space domain. A CA is consists of cellular, cellular space, neighbor, and some rules.

The basic cell in CA is called a cellular. A CA is a triplet, and can be defined as:

$$A = (S, N, \delta) \quad ...(1)$$

Here, S is a non-empty state set, N is the neighborhood system and is the rule. There are mainly two neighborhood models, one is the Von Neumann model and the other is the Moore model. The Von Neumann model is shown in Figure 2(a). In the model, each cellular has four neighbors, the upper one, the lower one, the left one, and the right one. The Moore model which is shown in Figure 2(b) is an eight-neighborhood system.

RGB_p

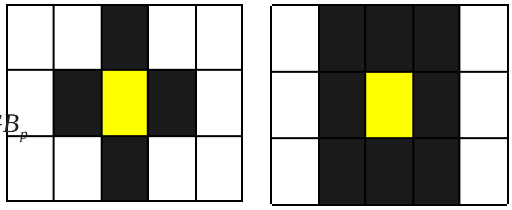


Fig. 2. The Von Neumann model and the Moore model

The rule is an evolution basis of a dynamic system whcih is a dynamic function of the next time in a cellular state.

A digital image is a two-dimensional array with $m \times n$ pixels, and can be considered as several particular state of CAs, where the cellular space P is defined as:

$$l_p = 0, \theta_p = 0, \vec{C_p} = RGB_p \quad ...(2)$$

Here, is the color space of pixel p, and the final goal is to assign labels to each pixel.

When user starts the segmentation by choosing the initial seeds, their strength is set to the seed strength value. The iteration procedure is shown as below.

Function Automata evolution rule

1 BEGIN

2 For $\forall p \in P$

$I_p^{t+1} = I_p^t$

$\theta_p^{t+1} = \theta_p^t$

For $\forall q \in N(p)$

If $g(\|\vec{C}_p - \vec{C}_q\|_2)\cdot \theta_q^t > \theta_p^t$

$I_p^{t+1} = I_q^t$

END IF

$\theta_{p+1}^t = g(\|\vec{C}_p - \vec{C}_q\|_2)\cdot \theta_q^t$

END For

END For;

END

Here, g is a monotonous decreasing function bounded to [0, 1]. The literature (Vezhnevets *et al*., 2005) uses the follow energy function:

$$g(x) = 1 - \frac{x}{\max \|\vec{C}\|_2} \qquad ...(3)$$

Although the principle of Grow-Cut algorithm is simple, it can segmentation an image with high precise. However, there is a drawback in it, particularly for medical image with fuzzy edge. The segmentation result is usually accompanied with burr, which is hard to accept for medical image process, for the sake that doctors can diagnose diseases with the smooth degree. In order to obtain a smooth segmentation result, literature (Vezhnevets *et al*., 2005) proposed a patulous Grow-Cut approach, which add two additional terms to the local transform function: one is that if a cell is surrounded with too many enemies, and meets the condition that $enemies^t(p) \geq T_1$, and then it is prohibited to attack its neighbor cells; the other is that if the number of a cell's neighbor enemies meets $enemies^t(p) \geq T_2$.

$$enemies^t(p) = \max_{l=1,K}\Big(\sum_{q\in N(p),\, l_q^t \neq l_p^t} l\Big) \qquad ...(8)$$

The threshold and T_2 control the smooth of the edge. The result is shown in Figure 3.

K-means

There are many tissues and organs distributed in the abdominal image, and among them liver is the most interested one. As the gray of liver is much

T_1

Fig. 3. The segmentation result of Grow-Cut algorithm

differ from skeleton and some other tissues, we can take a clustering operation before a segmentation operation, in order to wipe out irrelevant tissues and accelerate the algorithm speed. Cluster analysis is a kind of algorithm, which takes into account the data similarity and classifies them. The similarity measurements in medical image are commonly gray, distance and texture.

K-means algorithm is a common image segmentation algorithm, which aims to partition N observations into number of K disjoint sub-set S_j, in which each observation belongs to the cluster with the nearest mean so as to minimize the sum of squares criterion:

$$J = \sum_{j=1}^{K}\sum_{n\in S_j}\left|x_n - \mu_j\right|^2 \qquad ...(4)$$

In Equation (4), x_n is a vector representing the n^{th} data point, u_j is the geometric center of the data points in S_j.

The specific flow of the K-means algorithm is described as:

(1) Choose points and set them as central points of each category using the input number k form the user.

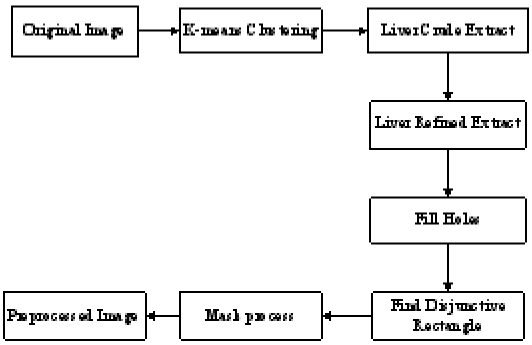
(2) For each point, calculate its Euclidean distance to the above k points, and set its label as the point of the shortest Euclidean distance.

(3) Find the new central point in each category, which meets that it owns the shortest Euclidean distance to other points in the same category.

(4) Repeat (2) and (3) until the central point in each category stops to change.

Image Preprocess by K-means Algorithm

Grow cut is a kind of bacteria survive competition algorithm, and its iteration termination condition is that the bacteria competes to a stable state. There are too many irrelevant regions in an abdominal image, which leads to reduce the process velocity and segmentation precise. Therefore, we should make a cluster analysis before devoting Growing algorithm to manipulate an image. The outline of the process procedure is shown as Figure 4.



70

Fig. 4. The procedure of image pre-process by K-means algorithm

Firstly, an image is manipulated by K-means algorithm, and each pixel in the image is labeled; Secondly, we extract the regions whose label is the same with the liver region; Thirdly, a candidate liver region can be obtained with the principle of the liver region owns the maximum area. As the K-means operation is based on the gray, although the liver region owns an integral gray similarity, there are some pixels owns a different gray level compared to the whole. Therefore, some holes need to be filled after obtaining the candidate liver region; then, we calculate a disjunctive rectangle of the filled candidate lever region, and lastly, we make a mask operation to extract the final result. The result is shown in Figure 5. In Figure 5, (a) is for an original image, (b) is for the image processed by K-means, (c) is for the liver crude extract image, (d) is for liver refined extract image, (e) is for the holes filled image and (f) is for the final pre-processed image.

The size of the original image is 128×128, while the size of the candidate liver image is . Use this image as an initial Grow-cut input image, which can efficiently improve the process velocity and increase the segmentation precise with the help of K-means pre-process algorithm.

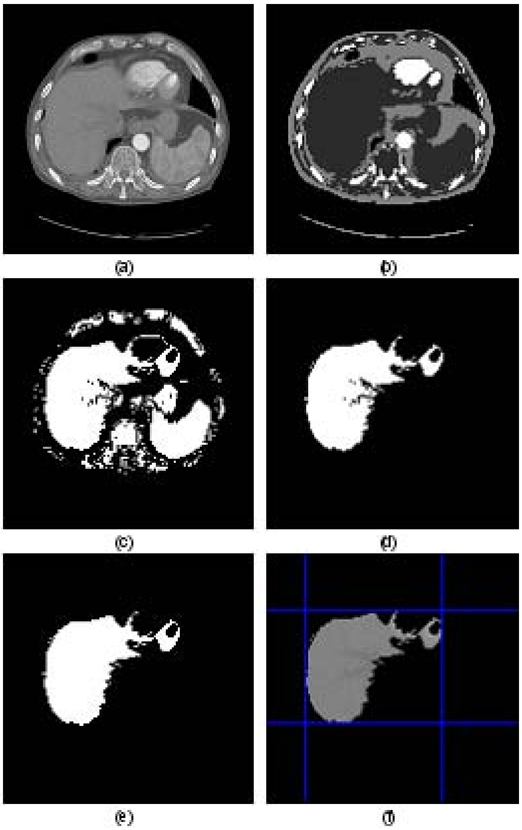


Fig. 5. Results of image pre-process by K-means algorithm

The proposed algorithm

The Improved Grow-Cut Approach

The Energy function is essential to the Grow-Cut algorithm. A common one which is shown is the equation (3) is widely used in recent years. As the energy function in (3) only takes the gray difference between the seed point and its neighborhood into account. It uses this difference to compute the competitiveness, and it can hardly make full use of the image information. With the need of high precise of medical image, in this paper, we introduce a novel energy function, which possesses better performance than the traditional one. The new energy function is defined as:

$$B_{\{p,q\}} = \exp(-\frac{(I_p - I_q)^2}{2\sigma^2}) \cdot \frac{1}{dist(p,q)} \qquad ...(5)$$

In the equation (5), B indicates the energy of any pixel and its neighborhood in an image, I_p, I_q respectively represent a pixel and its neighbor pixel, σ^2 is a covariance value between a pixel and its neighbor pixels, $dist(p,q)$ is the distance of a pixel and its neighbor pixel.

The energy function (5) owns two benefits: one is that it not only considers the gray difference between two pixels, but also takes the difference intense between the seed point and its neighbor pixels into account. The larger value of σ^2, the higher change degree of neighbor pixels of the seed point. In the same way, we can get strong competitiveness, which can help to accelerate the competing among germ and benefits to get a balance. The second value of the novel energy function is that the equation (5) sets the competitiveness in inverse proportion to the distance between two pixels, which is more accord to the real case of germ compete in the environment, and is more benefit to solve the problem of edge detection.

The procedure of the algorithm is shown as below. We take energy function as a measure criterion, and the iteration will stop at the time of the energy minimization.

The germ compete environment in literature (Vezhnevets *et al*., 2005) is the overall image, which costs much time to split. However, most time spent in this step can be saved. Based on this reason, we do a pre-extraction of our interesting region and we only manipulate this region with Grow-Cut algorithm. By the aid of such a pre-process, a large amount of time can be saved and the segmentation precise has been largely enhanced.

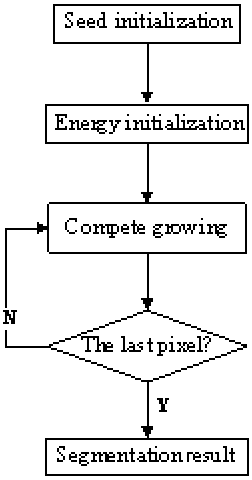


Fig. 6. The procedure of our Grow-Cut method

Multi-region Segmentation Based on The Improved Method

The seed point of traditional Grow-Cut approach owns only two kinds: the foreground points and the background points. Therefore, only a particular region can be got when the germ comes to a balance state. In our work, we focus on the segmentation of medical image. So we set the initial seed point into four kinds: liver, spleen, left kidney, right kidney. Then, when the germ gets a balance after competing, we can get the above four interesting regions with good result.

Experiments and analysis

The experimental data is 30 abdomen CT image with format of DICOM derived from a 64 row CT machine in a domestic large hospital which space resolution is 512×512. In order to improve the speed, we convert the DICOM images into BMP images, whose gray level is 256 and space resolution is 512×512. Experiments are carried out in a computer with Pentium processor of 3.0GHz and memory of 1GB. The particulars of datasets are shown in Table 1

Table 1. Particulars of Datasets

Item	Instruction
Image Modality	CT scan
Format	BMP
Anatomy	Liver
Acquisition Phase	Arterial and Portal Phase
Size	512×512

Single Region Segmentation of Medical Image

Figure 7 shows the segmentation result of some medical image with only one interesting region. In Figure 7, (a) and (b) are two original images, (c) and (d) are the corresponding segmentation results based on the traditional graph-cut method, (e) and (f) show the results of our proposed algorithm. We carry out experiments with liver CT images to demonstrate the performance of the proposed segmentation approach, and compare the proposed results with the results of the traditional graph cut method. We can see that in Figure 7 (c) (d), the boundaries of regions are not very smooth, and many pixels around the left lobe are misclassified. As shown in Figure 7 (e) (f), the result of the proposed algorithm demonstrates a visually significant improvement and robustness to noise, and preserves better edge information than the former approach. The number of misclassified pixels is less than that of the contrastive algorithm. However, there exists owe segmentation problem in the left lobe of the liver and the segmentation accuracy in some CT image with complicated organs still need to be improved.

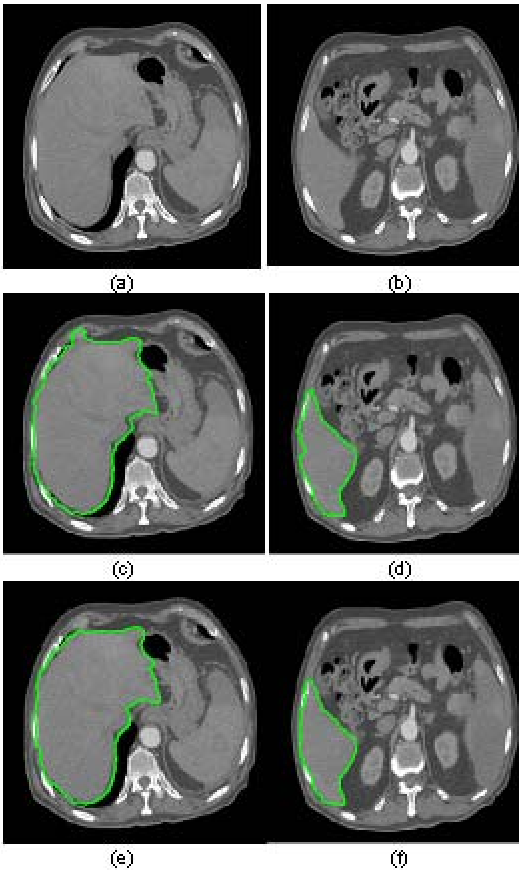


Fig. 7. The segmentation result of medical image

Table 2 shows an average case of 30 sets of abdomen CT images in time, iteration times and segmentation accuracy.

Table 2. Comparison about The Two Algorithm

Method	Time/s	Accuracy
Graph-Cut	0.88	85.6%
The Proposed Method	0.51	91.6%

Multi-Region Segmentation of Medical Image

The seed point of traditional Grow-Cut approach owns only two kinds: the foreground points and the background points. Therefore, only a particular region can be got when the germ comes to a balance state. In our work, we focus on the segmentation of medical image. So we set the initial seed point into four kinds: liver, spleen, left kidney, right kidney. Then, when the germ gets a balance after competing, we can get the above four interesting regions with good result.

As the traditional graph cut algorithm is difficult to solve the problem of multi-regions segmentation. Our proposed algorithm can solve such problem efficiently.

As shown in Figure 8, our algorithm can efficiently manipulate image with multi-region.

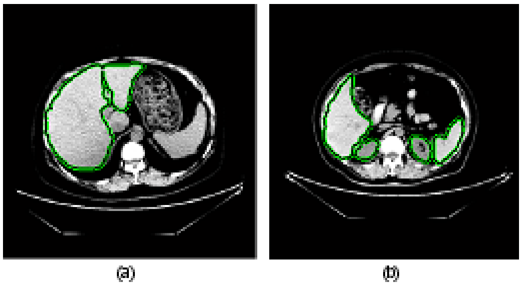


Fig. 8. The segmentation result of multi-regions

CONCLUSIONS

Aiming at the segmentation of liver region in the abdomen CT image, we propose a novel algorithm based on Grow-Cut. The Grow-Cut is an iterative algorithm, as the automation labels the image, user can observe the segmentation evolution and guide the algorithm with human input where the segmentation is difficult to compute. In this paper, we propose a new energy function for the traditional Grow-Cut method to obtain the better segmentation precision. Moreover, we do a pretreatment using the K-means to decrease the running time. In additions, we take multi labels for the Grow-Cut to get multiple organ segmentation results in one operation. Lastly, we take several experiments to demonstrate the validation of our proposed algorithm, and we choose the traditional graph cut as the contrast algorithm. Experimental results show that our method has a good robustness and better segmentation precise than the traditional graph cut method.

ACKNOWLEDGEMENT

The research is supported by the National Natural Science Foundation of China (No.61272176 and No. 60973071).

REFERENCES

1. Basak J, Chanda B., On Edge and Line Linking with Connectionist Models. *Pattern Analysis and Machine Intelligence*. 1994; **24**(3): 413-428.
2. Boykov Y, Jolly MP., Interactive Graph Cuts for Optimal Boundary and Region Segmentation of Objects in N-D Images. ICCV'01, Vancouver, British Columbia,Canada, 2001: 105-112.
3. Chen CW, Luo JB, Parker KJ., Image Segmentation via Adaptive K-means Clustering and Knowledge-based Morphological Operations with Biomedical Applications. IEEE Trans Image Process. 1998; **7**(12): 1673-1683.
4. Chang YL, Li XB., Adaptive Image Region-Growing, *IEEE Trans Image Process*. 1994; **3**(6): 868-872.
5. Cohen FS, Copper DB., Simple Parallel Hierarchical and Relaxation Algorithms for Segmenting Noncaual Markovian Random Fields. *IEEE Trans Pattern Anal Mach Intell.* 1987; **9**(2): 195-219.
6. Cross GR, Jain AK., Markov Random Field Texture Models, IEEE Trans Pattern Anal Mach Intell. PAMI 1983; **5**(1): 25-39.
7. Geman S, Geman D., Stochastic Relaxation Gibbs Distribution, and The Bayesian Restoration of Images, *IEEE Trans Pattern Anal Mach Intell*. 1984; **6**(6): 721-741.
8. Lin JS, Chen RM, Huang YM., Medical Image Segmentation Using Mean Field Annealing Network. *International Conference on Image Processing (ICIP'97).* 1997; **2**(9): 855-858.
9. Grady L, Gareth FL., Multi-label Image Segmentation for Medical Applications Based on Graph-Theoretic Electrical Potentials.Proc. of ECCV Workshops CVAMIA and MMBIA, 2004; **33**(17): 230-245.
10. Neumann JV., Theory of self-reproducing automata. University of Illinois Press. Ed. and Completed by A. Burks, 1966.
11. Rezaee MR, van der Zwet PJ, Lelieveldt BP, van der Geest RJ, Reiber JH., A Multisolution Image Segmentation Technique Based on Pyramidal Segmentation and Fuzzy Clustering. *IEEE Trans Image Process*. 2000; **9**(7): 1238-1248.
12. Reese L., Intelligent Paint: Region-based interactive image segmentation. Master's thesis, Department of Computer Science, Brigham Young University, Provo, UT, 1999.
13. Rick Chartrand, Kevin R. Vixie, Brendt Wohlberg, Erik M. Bollt., A Gradient Descent Solution to The Monge-Kantorovich Problem*, Applied Mathematical Science,* 2009; **3**(22): 1071-1080.
14. Sahoo PK., Soltani S, Wong AKC, Chen YC., A Survey of Threshold Techniques. Computer *Vision Graphics and Image Processing*, 1998; **41**(2): 233-260.
15. Sahoo P, Wilkins C, Yeager J., Threshold Selection Using Rrenyi's Entropy. *Pattern Recognition*, 1997; **30**(1): 71-84.
16. Vezhnevets V, Konouchine V., GrowCut-Interactive Multi-label N-D Image Segmentation by Cellular Automata. *Proc. Graphicon*. 2005; 150-156.