Medical Image Segmentation Based on Watershed and Graph Theory

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***Abstract*—Strong noise, poor gray-scale contrast, blurred margins of tissue are characteristics of medical images. Extracting object of interest in medical images is challenging. A segmentation approach that combines watershed algorithm with graph theory is proposed in this paper. This algorithm reconstructs gradient before watershed segmentation, based on the reconstruction, a floating-point active-image is introduced as the reference image of watershed transform. Finally, a graph theory based algorithm Grab Cut is used for fine segmentation. False contours of over-segmentation are effectively excluded and total segmentation quality significant improved as suitable for medical image segmentation.**

Keywords-medical images; watershed algorithm; floating-point active-image; Grab Cut method

I. INTRODUCTION

Nowadays, imaging technology such as computerized tomography (CT), ultrasonic (US) and magnetic resonance imaging (MRI) plays an irreplaceable role in medical diagnosis, pathology research, operation planning and post operation observation. Correctly extract the object of interest is an important step, which can pave the way to successful medical diagnosis and analysis.

Generally speaking, medical images have such characteristics as strong noise, poor gray-scale contrast and blurred margins of tissue. The common threshold and edge detection segmentation often fails to give quality separations for the object of interest. Recent research show that watershed segmentation is comparatively fit for medical image segmentation because of its unique regional margin locating and closed contour extracting capability [1, 2, 3]. As for watershed algorithm [4], usually, watershed algorithm is applied on the morphological gradient of the image that is going to be segmented. Each independent regional minimum of the gradient image is grouped into different region when morphological gradient image is segmented by watershed algorithm, which finally leads to "over-segmentation", that is, too many false contours appear to identify the real contour.

In recent years, a number of researchers improve watershed algorithm to solve the problem of "over-segmentation" [5, 6]. In order to improve the over-segmentation phenomenon, the medical image segmentation based on the combination of watershed algorithm and graph theory is proposed in this paper. This algorithm reconstructs gradient before watershed segmentation, based on the reconstruction, a floating-point active-image is introduced as the reference image of watershed transform. Finally, a graph theory based algorithm Grab Cut is used for fine segmentation. False contours of over-segmentation are effectively excluded and total segmentation quality significant improved as suitable for medical image segmentation.

II. MEDICAL IMAGE SEGMENTATION BASED ON WATERSHED ALGORITHM AND GRAPH THEORY

A. Algorithm procedure

The algorithm procedure in this paper is as follows.

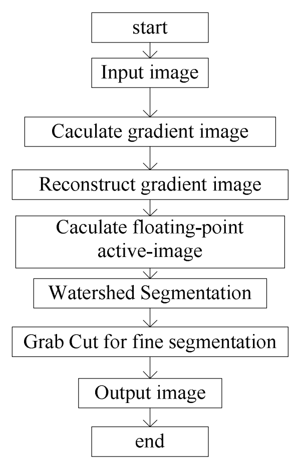

Figure 1. The procedure of algorithm

B. Reconstruct Gradient Image

Watershed segmentation algorithm: extract the regional minimum from the image, and then ascertain the watershed line corresponding to that minimum. The watershed line reflects the boundary of the sudden change of intension in the image. Since attention is usually paid to the size of the gradient image, the reference image in watershed transform is the gradient image that employs the calculation of morphological dilation and erosion. The gradient image ***g(x, y)*** of the image ***f(x, y)*** is:

$$g(x,y) = f(x,y) \oplus B - f(x,y) \Theta B \tag{1}$$

Where ***B*** is a disc-shaped structural element. As disc-shaped structural elements are isotropic, they can eliminate the dependence of gradient on the edge-orientation; meanwhile, structural elements have small radius, thus can avoid excessively thick edges appearing in gradient images which can result in errors of regional contour location. But noise and details still exist in morphological gradient image. If watershed segmentation is used directly, it will lead to serious over-segmentation. Therefore, we need reconstruct gradient image.

In this paper, gradient image is reconstructed by morphological mixed opening and closing reconstruction operation, which can eliminate regional extremum in gradient image caused by irregular gray-scale disturbance and noise and retains extremum information of important contours. Traditional morphological opening and closing operation can only remove regional details in parts of high and low gray-scale in images, while opening and closing reconstruction operation in the process of smoothening images can completely remove or retain regional details in high and low gray-scale which is smaller than the current size [7].

Morphological opening and closing reconstruction operation is based on geodesic erosion and geodesic dilation. As for gradient image ***g(x, y)*** and reference image ***r(x, y)*** (it refers to the original input image in this algorithm), the definition of the morphological geodesic dilation is [8, 9]:

$$\begin{cases} D_B^{i+1}[g(x,y),r(x,y)]=Min[(D_B^i \oplus B),r(x,y)] \\ D_B^1[g(x,y),r(x,y)]=Min[[g(x,y)\oplus B],r(x,y)] \end{cases} (i=1,2,...) \qquad (2)$$

Likewise, the morphological geodesic erosion of $g(x,y)$ is defined as:

$$\begin{cases} E_B^{i+1}[g(x,y),r(x,y)]=Max[(E_B^i \Theta B),r(x,y)] \\ E_B^1[g(x,y),r(x,y)]=Max[[g(x,y)\Theta B],r(x,y)] \end{cases} (i=1,2,...) \qquad (3)$$

Both morphological geodesic erosion and dilation are iteration operation. Based on the definition of geodesic erosion and dilation, morphological opening operation reconstruction ($O_B^{(rec)}$) and morphological closing operation reconstruction ($C_B^{(rec)}$) are respectively defined as:

$$O_B^{(rec)}[g(x,y),r(x,y)] = D_B^{(rec)}[[g(x,y)\circ B],r(x,y)] \qquad (4)$$

$$C_B^{(rec)}[g(x,y),r(x,y)] = E_B^{(rec)}[[g(x,y)\bullet B],r(x,y)] \qquad (5)$$

Where $\circ$ and $\bullet$ are morphological opening and closing operation respectively; $D_B^{(rec)}$ and $E_B^{(rec)}$ are the constringency results of morphological geodesic dilation and erosion respectively. In this algorithm opening and closing reconstruction operation are combined to construct morphological mixed opening and closing reconstruction operation, and thus to eliminate the light and dark details and noise in the image at the same time. Morphological mixed opening and closing reconstruction operation is defined as:

$$O_B^{(rec)}[g(x,y),r(x,y)] = D_B^{(rec)}[[g(x,y)\circ B],r(x,y)] \qquad (6)$$

Morphological opening reconstruction operation is firstly employed to eliminate the maximum noise and irregular disturbance whose size is smaller than structural elements in the gradient image, and then morphological closing reconstruction operation is employed to remove dark noise and irregular disturbance which is smaller than structural elements. Morphological mixed opening and closing reconstruction operation corrects regional maximum and minimum, reduces even eliminates the watershed line excursion caused by details and noise disturbance, has precise contour locating capability, reduces the excursion of regional contour lines and obviously improve the watershed over-segmentation phenomenon caused by too many regional minima.

C. Floating-point active-image operation

Introduce floating-point active-image on the basis of the reconstructed gradient image, and continually optimize the reference image in watershed algorithm.

Floating-point active-image is from morphological gradient image. “Floating-point” means that the image data are float. Floating-point active-image has comparatively high light data near to the boundary point of the article, and there are comparatively low and even light data inside of the article, therefore, floating-point active-image itself reflects the rough contour information of the article. Floating-point active-image can be obtained from the following formula:

$$fimg(I) = g(x,y)\times g(x,y)/b \qquad (7)$$

Where ***b*** is a changeful constant ranging from 0.0 to 255.0, and its scale in experiments is usually from 4 to 30. ***g(x, y)*** in the formula is assigned by $G_B^{(rec)}$, that is, use the reconstructed gradient image for floating-point active-image operation. This not only reduces the unnecessary details in the reference image, but also expresses the image contour information better. If used for watershed segmentation, it can restrain over-segmentation more effectively.

D. Grab Cut for fine segmentation

In recent years, image segmentation based on graph theory has aroused growing interest. There are Graph Cuts [10], Normalized Cut [11], Dominate Set [12] and Mountain Standard Time (MST) [13], to name a few. One of their common features is to regard the pixel in images as one feature point. Then classify these points by means of clustering or grouping, and thus finish the image segmentation [14]. Since Graph cuts are proposed, many excellent algorithms have appeared, Grab Cut included. Grab Cut is good both in the segmentation result and implementation efficiency.

Grab Cut has made three improvements on the basis of

Graph cuts. First, use Gaussian Mixture Model (GMM) to replace the histogram to describe the distribution of foreground and background pixels, and process colored images instead of gray images; secondly, use iteration to obtain the parameters in GMM to replace the operation process that completes energy minimization through one-time minimum estimation; thirdly, reduce users' workload in their exchange process through non-full mark. The basis algorithm process of Grab Cut is as follows [15]:

1) Initialization process: Users can initialize the trimap by setting the background region; give 0 as the Alpha value of the pixel in all background regions, give 1 as the Alpha value of the pixel in unknown regions; use two sets, $a_n = 0$ and $a_n = 1$ to initialize the foreground and background of GMM respectively.

2) Minimization process through iteration: The image is an array of "opacity" values $\underline{a} = (a_1, ..., a_N)$ at each -pixel.Generally $0 \le a_n \le 1$, but for hard segmentation $a_n \in \{0,1\}$, with 0 for background and 1 for forground. The parameters $\underline{\theta}$ describe image foreground and background grey-level distributions, and consist of histograms of grey values. In order to deal with the GMM tractably, in the stage of minimization process, an additional vector $k = (k_1, ..., k_n, ..., k_N)$ is introduced, with $k_n \in \{1, ..., k\}$, assigning, to each pixel, a unique GMM component, one component either from the background or the foreground model, according as $a_n = 0$ or $a_n = 1$.

a) *First:* To obtain each pixel of the regions, set the parameter formula of GMM as follows:

$$k_n = \arg\min_{k_n} D_n(a_n, k_n, \theta, z_n) \tag{8}$$

b) *Second:* Obtain the parameter of GMM by the data of pixels in images. The formula is as follows:

$$\underline{\theta} = \arg\min_{\underline{\theta}} U(\underline{a}, k, \underline{\theta}, z) \tag{9}$$

c) *Third:* Get the initial segmentation by minimizing energy. The minimum energy is as follows:

$$\min_{\{a_n : n \in T_U\}} \min_{k} E(\underline{a}, k, \underline{\theta}, z) \tag{10}$$

d) *Fourth:* Return to Step 1 and repeat the process till the convergence.

e) Finally: Optimize the boundary.

3) Users Edit: Firstly, edit and give Alpha values to some pixels. Suppose $a_n = 0$ and $a_n = 1$, update the trimap, and then implement Step 3 of the minimization through iteration. Finally, operate optimization and implement the whole minimization process through iteration, which can be omitted and is optional.

In this paper Grab Cut is used as the method of fine segmentation. It solves not only the problem of over-segmentation but also the problem of a large amount of computing.

III. Experimental Results and Analyses

A typical CT test image of human pelvic cavity bone and a typical CT test image of human finger are used for segmentation experiment. The size of these images is 256×256 pixels, and the gray level is 8 bits. The experiment result is shown in Figure 2.

The first row and the third row show the original images and their floating-point active-image; the second row and the end row show segmentation results of common watershed and our algorithm. Reduction of segmentation fragment is evident.

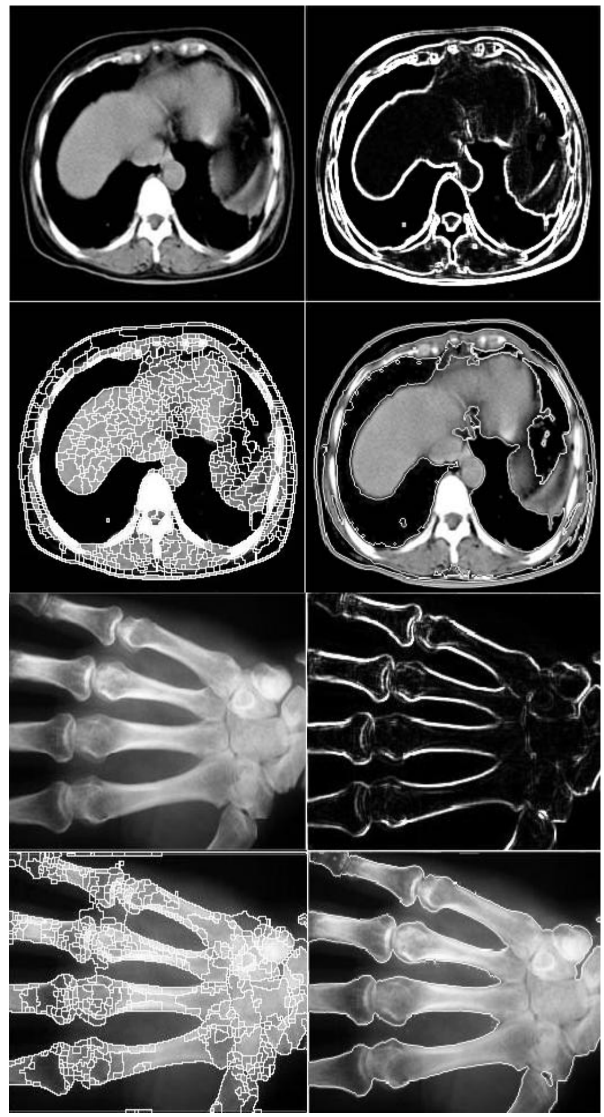

Figure 2. Experiment results and segmentation comparisons

From Graph 2, we know that the floating-point active-image is calculated after the reconstruction of gradient image. Then use the floating-point active-image as the reference image of watershed segmentation, after which use Grab Cut for fine segmentation. Compared with traditional watershed algorithm, this algorithm doesn't only improve over-segmentation phenomenon of watershed algorithm and the problem of large data during segmentation which use Grab Cut algorithm directly, but also retain detailed information as much as possible.

IV. CONCLUSION

The quality of segmentation directly exerts an influence on the successive processing and analyzing. Especially for medical images, segmentation is a key step in the medical image analysis and diagnosis. This new algorithm that combines morphological mixed opening and closing reconstruction operation with float-point active-image operation to improve traditional watershed algorithm, and then used fast Grab Cut algorithm for fine segmentation. The experiment results are satisfactory. We believe that our combinational segmentation method provide an excellent alternative for medical image segmentation.

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