A High-speed Method for Liver Segmentation on Abdominal CT Image

Wenhan Wang
School of Electronic and Information Engineering
Liaoning Technical University
Huludao, China
yuoiobest@gmail.com

Xihe Gao
Northeastern University
Shenyang, China
xihe.gao@gmail.com。

***Abstract*—This paper presents a high-speed liver segmentation method applied on abdominal CT image. Firstly, based on the morphological feature of the liver region under various window-level settings, we apply the region-growing algorithm to remove other tissues such as skeleton, skin, kidney and stomach, and hence the discrete points of the liver region can be acquired. Secondly, we recover the liver region from the original image by calculating the coordinates of the discrete points. Finally, in order to get more accurate segmentation results, the gradient information based edge correction and three-dimensional restoration are adopted to optimize the recovered liver image. Compared with other liver segmentation methods, our method has lower time complexity, which can satisfy the demands of real-time processing.**

Keywords- ***image segmentation; liver; window-leveling technique; three- dimensional restoration***

I. INTRODUCTION

In the last two decades, modern imaging techniques contributed to the medical progress by improving the possibilities of technical imaging. The improvement provides deeper insight into the human body and its bio-medical processes, leading to the development of novel scientific interests in promoting the diagnosis. Besides, the modern imaging techniques produce a large amount of image materials which need to be analyzed by the physicians. Both the new scientific methods and the large amount of image data require the assistance of the computer with regard to automatic image analysis.

There are increasing interests for automatic image analysis in many domains, and for the reason that the accurate segmentation of liver from the computed tomography (CT) image can serve as the prerequisite for hepatic disease diagnosis and surgery planning, the automatic liver segmentation has become an important research topic [1-5]. Several methods are proposed for the liver segmentation from CT images. Parametric active contour models (Snakes) have been applied often for the segmentation of the liver region [6, 7]. Also, its variational reformation as geometric active contour models can achieve even better performance during the liver segmentation process regarding topological change [8, 9]. Nevertheless, the segmentation methods suffer from certain drawbacks. The sensitivity to the initial contour makes it difficult for the snake model based segmentation method to get satisfying results. And for images with intensity inhomogeneity, the liver segmentation results of the geometric active contour models are far from perfect. Moreover, these liver segmentation methods based on active contour model have high time complexity and can hardly satisfy the real-time processing.

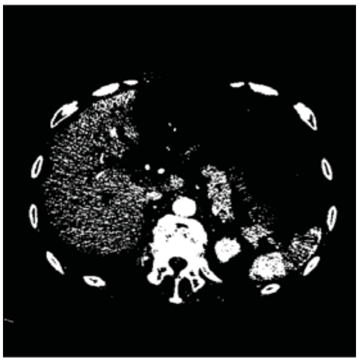
In this paper, we propose a high-speed segmentation method which makes use of basic image processing techniques such as the region-growing algorithm and combines them with further ideas. In contrast to other liver segmentation methods, our method can obtain satisfying results with lower time complexity.

II. LIVER SEGMENTATION METHOD

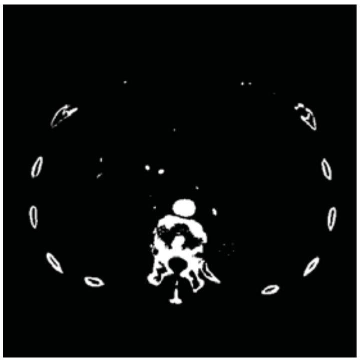
A. Image preprocessing

The CT image has high resolution and its gray scale is 12 bits (4096 gray levels). We map the raw image to the range of [0, 255] by applying the window- leveling algorithm. According to the prior knowledge of liver, the value of window width is set at 255 and the value of window level is set at 100. The transformed image is shown as Fig.1 (a).

(a) The transformed image



(b) The discrete liver image



(c) The evanescent liver image

(d) The discrete points of the liver region

Figure 1. Results in the preprocessing

In the same way, when the value of window width is 2, the CT value lower than the widow level will be set to 0 while the value higher will be set to 255. The morphological feature of liver is diverse under different settings of the window level. If the window level is set at L_s, the liver region is presented as discrete points called discrete liver image. In the discrete liver image, the liver region can be distinguished from other tissues. Also, if the window level is set at L_e, the liver region is totally evanescent and this image could be called evanescent liver image. The discrete liver image and the evanescent liver image are represented in Fig.1 (b) and Fig.1 (c) respectively.

Further analysis indicates that the window level setting is positive proportional to the average gray value of the liver region, and the window settings for discrete liver image and evanescent liver image can be expressed by the average gray value. Then, if the average gray value is denoted by G_{mean} and the radios for discrete liver image and evanescent liver image are denoted by k_1 and k_2 respectively, the values of L_s and L_e can be defined as:

$$L_s = k_1 G_{mean} \tag{1}$$

$$L_e = k_2 G_{mean} \tag{2}$$

In this paper, the statistical method has been used in order to determine the value of k_1 and k_2. We select 50 abdominal CT images as samples and segment the liver region manually so that the average gray value can be obtained. Then we calculate the corresponding ratio k_1 and k_2. According to the experimental results, the mean of k_1 is 1.18; the standard error of k_1 is 0.02; the mean of k_2 is 2.67; the standard error of k_2 is 0.03. Therefore, we can set the value of k_1 at 1.18 and the value of k_2 at 2.67 within the acceptable error range.

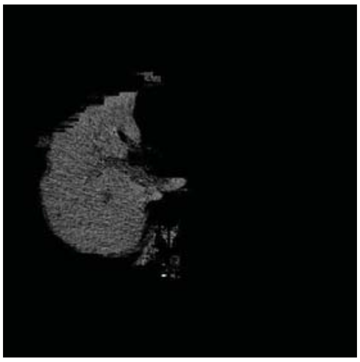
Nevertheless, in the obtained discrete liver image, other tissues such as skeleton and kidney still exist. Since the evanescent liver image is involved with the discrete liver image, we can use the evanescent liver image to remove the non-liver region in the discrete liver image. During the process, we adopt the region-growing algorithm in which the region presented in the evanescent liver image is selected as the set of seed points. Then, the results area of the region-growing algorithm is removed from the discrete liver image and the discrete points of the liver region shown in Fig.1 (d) can be achieved.

B. Recovering liver with the discrete points

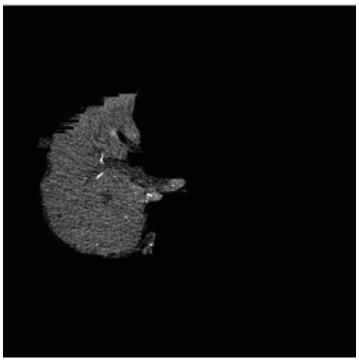
The preprocessing can bring the discrete points whose contour corresponds to the actual liver region. Therefore, with the help of the discrete points, we are able to recover the liver region from the transformed image. The image quality of the recovered liver is related to the dense of the discrete points. The denser the discrete points are, the more accurate liver image we can get. The recovering algorithm is described as follows.

First, we calculate the minimum coordinate and the maximum coordinate of the discrete points column by column, and then recover the pixel values between the minimum and the maximum from the transformed image. For the sake of avoiding the phenomenon of over-segmentation, the difference between any two adjacent coordinates should be less than the threshold denoted by d (d is set at 50 when the image size is 256×256).

Second, in the same way, we calculate the minimum coordinate and the maximum coordinate row by row and recover the corresponding pixel values from the transformed image. Also, the difference between any two adjacent coordinates should be less than d. The recovered liver image is represented in Fig.2 (a)



(a)The recovered liver image.



(b) The liver image after optimization

Figure 2. Segmentation results

1) Edge correction

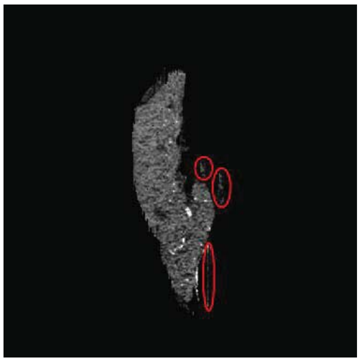
The recovered image obtained in the previous step has jogged edge and can hardly satisfy the demands on image quality. In order to solve the problem, we correct the image edge by using the gradient information. We record the minimum and the maximum of the coordinate row by row. In the neighborhood of the minimum and the maximum, we search for the pixel whose normalized gradient is higher than the threshold denoted by g . If the pixel does exist, we replace the minimum coordinate or the maximum coordinate with the coordinate of the pixel. Again, the pixel values between the revised minimum coordinate and the revised maximum coordinate are recovered from the transformed image.

2) Removing the over-segmentation

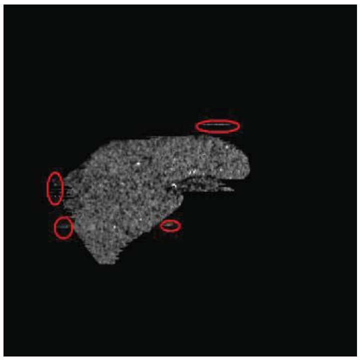
In this step, we apply the region-growing algorithm to calculate the number of pixels in each connected region. If there are more than one connected regions in the image, the connected region whose number of pixels is less than the threshold denoted by n will be removed from the recovered image, leading to the elimination of the over-segmentation. The optimized liver image has been shown in Fig.2 (b).

3) Three-dimensional restoration

The optimized liver image demonstrates that we can already get satisfying segmentation results. However, the complexity of the liver and the liver disease make it difficult to segment the liver region only based on the two-dimensional cross section. In order to achieve better performance in 3D visualization, we revise the previous segmentation results in three dimensions [10, 11]. Fig.3 (a) represents the sagittal liver image, while Fig.3 (b) represents the coronal liver image. The images indicate that over-segmentation marked with the red circle still exist in the obtained images. The region-growing algorithm can be used again to remove the connected regions whose number of pixels is less than n .



(a) The sagittal liver image



(b) The coronal liver image

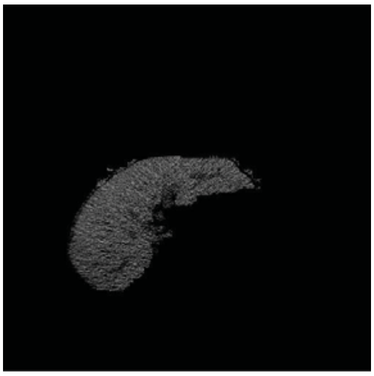
Figure 3. Results in three-dimensional restoration.

III. EXPERIMENTAL RESULTS

In order to explain the advantages of our method, we apply the method to medical images. Experimental data comes from abdominal CT images which are collected from a large hospital's 64-slice CT machine (spacing between layer: 2.0 mm, spatial resolution: 512×512, image format: DICOM).

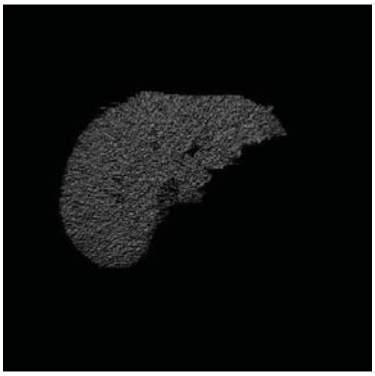
The algorithm is implemented in C++ and experiment environment is Windows XP, Pentium 4 CPU 3.0 GHz, 512 M RAM. According to the prior knowledge of liver, we select a specific area in three slices, and calculate the average gray value which can be used to stand for the average gray value of the whole group. g is set at 0.5, and n is set at 50. The liver segmentation results are shown in Fig.4. We compare our method with the level set model based segmentation method and the GVF snake model based segmentation method. As shown in the Table 1, our method is about 59 and 107 times more efficient than the GVF snake model based segmentation method and the level set model based method. We can also draw the conclusion that our method can satisfy the real-time diagnosis in terms of computational efficiency.

(a) The original image.



(b) The liver region obtained through our method

(c) The original image.



(d) The liver region obtained through our method

(e) The original image.

(f) The liver region obtained through our method

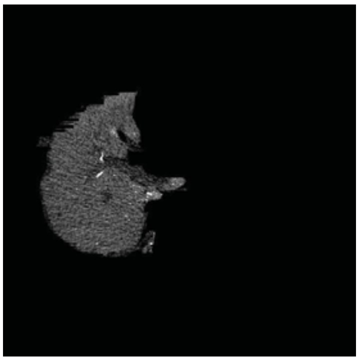
Figure 4. Segmentation results of our proposed method.

TABLE I. COMPARISON OF OUR METHOD, LEVEL SET MODEL BASED METHOD AND GVF SNAKE MODEL BASED METHOD IN CPU TIME

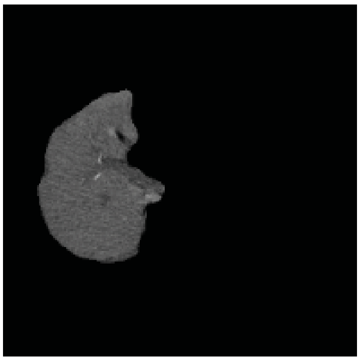
Method	CPU time(s)
GVF snake model	106.75
Level set model	191.75
Our method	1.8

Nevertheless, when compared with the segmentation results of the other two methods, our method has some limitations. For instance, there is still over-segmentation phenomenon in the liver image. The comparison of segmentation results have been shown in Fig. 5.

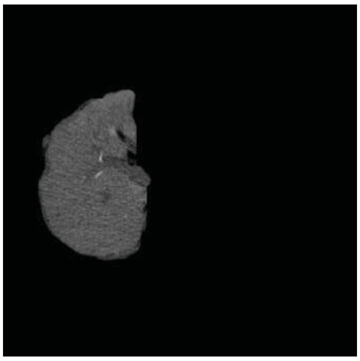
(a) The original image



(b) Proposed method



(c) Level set model based method



(d) GVF snake model based method

Figure 5. Comparison of segmentation results

IV. CONCLUSIONS

We propose a high-speed method for liver segmentation in this paper, and the application of the method proved effective in the automatic liver segmentation from abdominal CT images. In contrast to model-based segmentation methods, such as segmentation method based on level set model and segmentation method based on GVF snake model, our method is superior in efficiency and has more practical value. However, the segmentation results of the proposed method have some problems like over-segmentation. Therefore, how to get more accurate segmentation results will be focused on in our future research.

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