

# Automatic Liver Segmentation on CT Images

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**Abstract.** In this paper, a new coarse-to-fine framework is proposed for automatic liver segmentation on abdominal computed tomography(CT) images. The framework consists of two steps including rough segmentation and refined segmentation. The rough segmentation is implemented based on histogram thresholding and the largest connected component algorithm. Firstly, gray value range of the liver is obtained from image histogram, then the liver area is extracted from the rest of an image according to the largest connected component algorithm. The refined segmentation is performed based on the improved GrowCut (IGC) algorithm, which generates the label seeds automatically. The experimental results show that the proposed framework can efficiently segment the liver on CT images .

**Keywords:** Liver segmentation; CT images; Improved Grow-Cut ; Histogram thresholding.

## 1 Introduction

Automatic segentation for liver computed tomography (CT) images is an important part in computer-aided liver diagnosis. CT has been widely used for clinical diagnosis of hepatic disease because of its high resolution. Accurate liver segmentation from abdominal CT scans is critical for computer-assisted diagnosis and therapy, Generally, radiologists or physicians have to manually delineate the liver region slice by slice, which is tedious and time-consuming due to the large amount of data. There are mainly two reasons to explain this phenomenon. The first one is the intensity of the liver is similar to other organs or muscles. The other one is different patients or even on the same patient may exist variation in both shape and scale[1-8].

Recently, a large variety of methods have been developed to improve the liver segmentation procedure. These methods are commonly based on region growing, clustering, classification algorithms, deformable models or level sets, statistical shape models, probabilistic atlases, and graph cuts.

[3] proposed a 3D statistical shape model to segment the liver from CT images. They firstly used a training set of shapes to build up a statistical model based on iterative technique. Each shape used in building model is defined by some anatomically specific points sampled on the liver surface. Then they computed the

mean shape and positioning it on the image. After that, they apply adjustment to every single shape. However, because the shape of the liver is highly variable, it is difficult to select the landmarks and the authors did not evaluate their model in clinical.

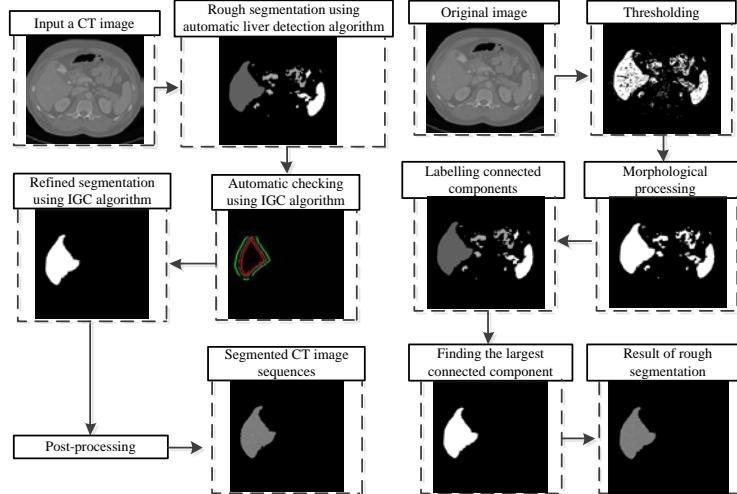
[2] proposed a region-growing approach. It can provide acceptable results on contrast enhanced CT images. The approach starts from a small region (environment of input curve, or point) and if the intensity of the neighboring voxel is corresponds to a pre-defined range, it will be added to the actual region. The region-growing method can close round the vessels and tumors efficiently (in contrast with active contour), but it's sensitive to select original input and if the intensity is similar , it is easily flow into the neighboring organs.

And [8] combined the methods of distance maps, thresholding and mathematical morphology to delineate the skin, bones, lungs, kidneys and spleen, then extracted the liver. They build a 3D reference model from manually segmented livers and adjusted into the image with rigid and affine registration. Then the model deformed to get the final result.

In this paper, an automatic liver segmentation framework without any interaction is proposed. Because different CT machines may generate different color ranges, a calibration step is needed for each different CT machine to perform automatic segmentation. The framework consists of two steps, rough segmentation based on automatic liver detection algorithm and refined segmentation based on IGC [9-11]. The rough segmentation is implemented based on histogram thresholding and the largest connected component algorithm. Firstly, gray value range of the liver is obtained from image histogram, then the liver area is extracted from the rest of an image according to the largest connected component algorithm. The refined segmentation is performed based on the improved GrowCut (IGC) algorithm, which generates the label seeds automatically. An automatic checking algorithm is proposed to choose the rough segmentation results which need to be done refined segmentation. The experimental results show that the proposed framework can segment the liver on the CT image series efficiently and automatically.

## 2 Methods

The proposed segmentation framework is shown in Figure 1. It consists of the following main steps. Firstly, the input CT image sequences are roughly segmented using automatic liver detection algorithm, then IGC is applied to do the refined segmentation. Various post-processing steps, such as filtering, filling holes, erosion and masking are implemented on the refined segmentation liver region.



**Fig. 1.** The proposed automatic liver segmentation framework (left) and **Fig. 2.** The flowchart of automatic liver detection (right)

## 2.1 Rough Segmentation using Automatic Liver Detection Algorithm

Since the intensity of the liver is similar with the adjacent other organs, without pre-processing, a direct liver extraction process may unavoidable extract undesirable components from its adjacent organs as fault positive/negative errors [1]. To solve this problem, we use the intrinsic characteristics of the liver. Because the liver is between the stomach, intestines and thorax in the abdomen. It is the largest organ in human body. Using these characteristics, our goal is to find the largest connected component in CT images.

The automatic liver detection algorithm consists of four main steps, thresholding, morphological processing, labeling and finding the largest connected component. The flowchart of the automatic liver detection algorithm is shown in Figure 2.

The original CT image, which is shown in Figure 3(a) was first processed by the thresholding method, which can be described as follows,

$$g(x, y) = \begin{cases} 1 & \text{if } (f(x, y) > T_1 \text{ and } f(x, y) < T_2) \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where  $g(x, y)$  is the image after thresholding operation,  $f(x, y)$  is the original gray-scale image,  $T_1$  and  $T_2$  are the intervals of the liver. The obtained threshold image is shown in binary image. Because the gray value range of the surrounding organs is similar to the liver, it may be connected with some other components which do not belong to the liver. In order to remove these surrounding components, which is shown in Figure 3(b), we perform morphological processing method on them, here we use erosion to remove the noise pixels in the image. Beacuse there are some pixels look like black holes exist in the component after erosion, another morphological pro-

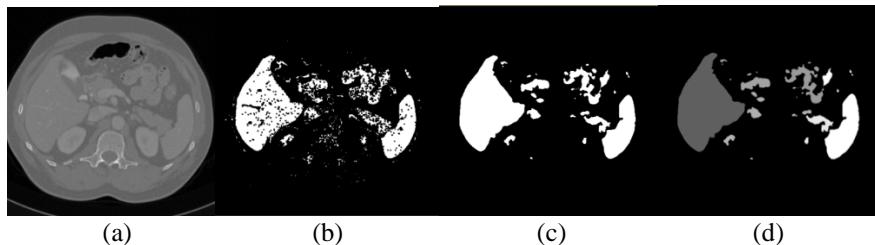
cessing approach is applied to fill these holes using flood filling and median filtering technology to make the image smoother. The median filter can be expressed as follows,

$$g(x, y) = \text{Median}(f_s(x, y)) \quad (2)$$

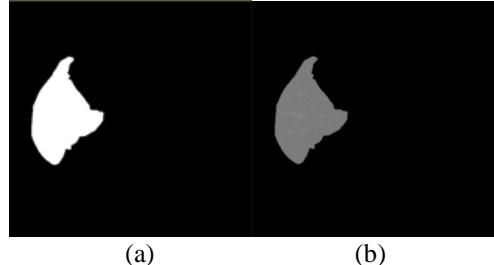
Where  $S$  is a temporary cluster in the whole image. It assumes a center pixel and create a  $3 \times 3$  or  $5 \times 5$  window with surrounding neighbor pixels.  $f_s(x, y)$  is the value of pixel in  $S$ ,  $(x, y)$  is the coordinate of the pixel.  $\text{Median}(f_s(x, y))$  is the middle value of all the values in  $S$ , which is used to instead the center pixel value. We can see from figure 3(c) that the morphological processing step can provide a smoother result with less irrelevant components and noise.

The next step is to label the connected component which has the same label. The labelling connected component algorithm is based on an iterative method. It searched the binary pixels in the image and labelled them with their adjacent labels according to the pixel's neighborhood. Usually there are two widely used neighborhood methods. One is the Moore neighborhood with 8-connectivity and another is von Neumann neighborhood which is using 4-connected pixels. The labelling algorithm first chose the binary pixels, marked them with current label and assumed these pixels as the center, then checked their neighbor pixels. If the value of neighbor pixel is binary, then the pixel is marked by the same label with the center pixel. The result of labeling the connected component is shown in Figure 3 (d).

In the last step, we know that liver is the biggest organ in the abdominal CT image, our task is to find the largest connected component in the image. Here we use the histogram of labeled images to automatic find the largest component because the liver accounted for most of the marked areas. Using this method we can extract the largest labelled component from all the labelled components and then get the liver area. The labeled result is shown in Figure 4(a). Using the labeled result multiplied by the original image, the final segmented result is shown in Figure 4 (b).

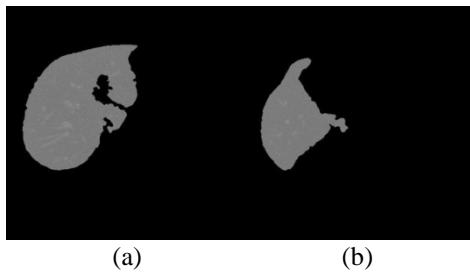


**Fig. 3.** (a) Original CT image, (b) Thresholded and erosed image, (c) Smooth image after morphologic processes, (d) The labeled connected components



**Fig. 4.** (a) The labeled result of the Liver, (b) The final segmentation result

However, some results of the above automatic liver segmentation algorithm are not smooth and accurate enough, such as under-segmented or over-segmented cases as shown in Figure 5. So refined segmentation is been used in the proposed segmentation framework after rough segmentation.



**Fig. 5.** (a) Under-segmented image, (b) Over-segmented image

## 2.2 Refined Segmentation Using IGC Algorithm with Automatic Checking

After rough segmentation, some images need to be refined. In order to find these images, We checked the total pixel number of an image and compared it with the previous one. By using thresholding methods, we got the images that need to be further segmented automatically.

In this comparison, if the difference between total pixel number of the current segmented image is more than the thresholding value, that means current segmented image has some problems, otherwise image does not need refined segmentation. When the algorithm detects any shrinkage between current segmented images and previous segmented images, connection method, which connects refined and rough segmentation, uses other predetermined threshold values to figure out whether the image need refination or not.

As mentioned above, the proposed segmentation method is totally automatic that decides which images need refination by using this algorithm. Rough segmentation with automatic liver detection is connected to refined segmentation with IGC automatically by this algorithm. In this paper, we applied the IGC algorithm to refine the rough segmentation results. The IGC algorithm was proposed by our research

group, which makes good use of the continuity of CT series in space and can automatically generate the seed labels to improve the efficiency of segmentation. The details about the IGC algorithm is given in the reference [12].

### 2.3 Post-Processing

After all these processes, some morphologic processes such as erosion and dilation are used to smooth edge of the image. Hereby the user can obtain the final result after post-processing.

## 3 Evaluation

Three groups of CT images were used to evaluate the segmentation performance. The slice thickness was  $1.0\text{ mm}$  and the spacing between slices was  $0.5\text{ mm}$ . Each slice had  $512 \times 512$  size. All segmentation framework were implemented in C++ language with OpenCV library on a 64-bit Windows 8.1 OS. All experiments carried on the computer with Intel(R) Core i7 (2.4 GHz), 8GB memory.

According to the experimental results, a dataset consists of around 200 CT images and this segmentation method handles all these CT images in 40-45 seconds.

The results of this automatic liver segmentation method (M1) is compared with another segmentation method (M2) which includes rough segmentation with SKFCM and IGC. For evaluation of these methods, there are three evaluation criterions, accuracy, overlap, and total process time of the method (PTM). Accuracy is a common criterion that is used to evaluate performance of segmentation methods widely. Overlap shows the degree of overlap between segmentation results by computer algorithm and manual segmentation results. The closer overlap is to 1, the better segmentation result will be. The accuracy and overlap are defined as follows,

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (3)$$

$$\text{Overlap} = \frac{TP}{TP + FP + FN} \quad (4)$$

where  $TP$  denotes the number of true positive pixels,  $TN$  denotes the number of true negative pixels,  $FP$  denotes the number of false positive pixels and  $FN$  denotes the number of false negative pixels.

**Table 1.** The Evaluation of Methods.

	Methods	Accuracy (%)	Overlap (%)	PTM (s)
Data 1	M1	99.69	94.61	42.12
	M2	99.58	94.48	102.45*
Data 2	M1	99.17	93.62	44.40
	M2	99.08	93.59	105.04*
Data 3	M1	99.67	93.73	41.28
	M2	99.69	94.16	100.67*

\* Interactions are not included in this process time.

The results show that the proposed automatic liver segmentation method is quite fast and reliable.

## 4 Conclusion

Liver diseases are a widely spread problem among all demographics of people. That is why we implemented a system related to the liver. Also in this project, we tried to remove all interactive methods and manual intervention. Thus, we proposed a full-automatic liver segmentation method.

The implementation consists of two main steps: rough segmentation with automatic liver detection and refined segmentation.

Firstly, in the rough segmentation, we used thresholding methods based on histogram to label the image and found the labeled largest components which finally identifies the liver. Therefore, we obtained the liver regions from all abdominal CT images.

Secondly, we used Improved Grow-Cut method to do refine segmentation for the under-segmentation or over-segmentation because of the blood vessels or similar surrounding tissues. We assessed a threshold to solve these problems which checked the change of the liver region pixels. If the pixel number of detected liver region increases or decreases over than the threshold value, we determined to refine concerned image slices with Improved Grow-Cut. Also, the method contains the automatic seed generation for Grow-Cut algorithm. That means we handled refined segmentation using Grow-Cut method without any interaction.

This fully automatic system does not contain any manual interaction so we hope these systems will be used widely in the clinical. In the future, these systems also can be combined with machine learning algorithms, thus the systems will recognize diseases without any doctors. Even some robotic systems can directly begin the treatment phase or surgery on the patients.

## 5 Acknowledgement

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