Liver Extraction from CT Images Based on Liver Structure Models

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Abstract—*The extraction of a liver from CT images is essential for oncologic surgery planning. This article presents an accurate and automatic approach to extract a liver from CT images. Our algorithm exploits three types of liver structure models: intensity model, shape model, and blood vessel model. First, the region including the liver is roughly extracted based on intensity histogram analysis. Second, the extracted regions are segmented using a shape feature called âĂİJlocal thicknessâĂİ based on the observation that the liver is thicker than other organs. Finally, the segmented regions including blood vessels in the liver are merged into a single liver region. Experimental results show that the average error of the volume extraction is 61.25 cc, and this result is much superior to the conventional one.*

Keywords: Medical imaging, 3D simulation analysis, anatomic hepatectomy, local thickness

1. Introduction

For liver cancer surgery, 3D simulation before surgery operations, recently, is getting one of the crucial tasks since a liver has complex structure. Liver segmentation is considered as a challenging task since the variations of the liver shape is large and since there exist some other organs with the CT values similar to the liver around the liver. There have been several researches on liver extraction[2]-[5]. The researches [2] and [3] use, respectively, statistical shape models and probabistic atlases, and both methods suffers from large variations of liver shapes. The active contour approach [4] are dependent on image gradient, and leads to over-extraction into organs with CT values similar to the liver. Moreover, its quality strongly relies on the location and shape of the initial contour. The intensity-based approach [5] usually exploits a simple intensity model, and miss the vessels and non-homogenous texture regions inside the liver.

This paper propose a new accurate intensity-based approach. In order to improve the quality, we use additional models: a shape and vessel models as well as an intensity one.
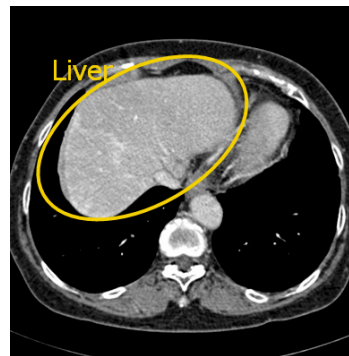

Fig. 1: CT image including the liver.

2. Liver structural model and extraction algorithm

2.1 Extraction of liver candidate regions based on an intensity model

Figure 1 shows a CT image of the liver. The liver is one of the biggest organs and the intensities of the liver points are evenly high. Figure 2 explains how the candidate regions of the liver are extracted based on the intensity model. First, the histogram of the intensity is computed as shown in the upper part of Fig. 2. The histogram has usually two mounts; the darker mount corresponds to the fat; the brighter one corresponds to the liver, spleen, born, etc. The brighter part is extracted automatically by using the Otsu' thresholding method[1]. Next, for the resulting 3D image, the thickness feature is measured by computing "Local Thickness" [6], where the local thickness of a point is defined as the diameter of the largest sphere that fits inside the object and contains the point, as shown in the lower part of Fig. 2. Since the liver region is large and thick, the region with largest local-thickness values is extracted as the core of the liver region. For this core region, the intensity histogram is computed to get accurate intensity thresholds for the liver region. Finally, the liver candidate regions are extracted by thresholding using the thresholds.
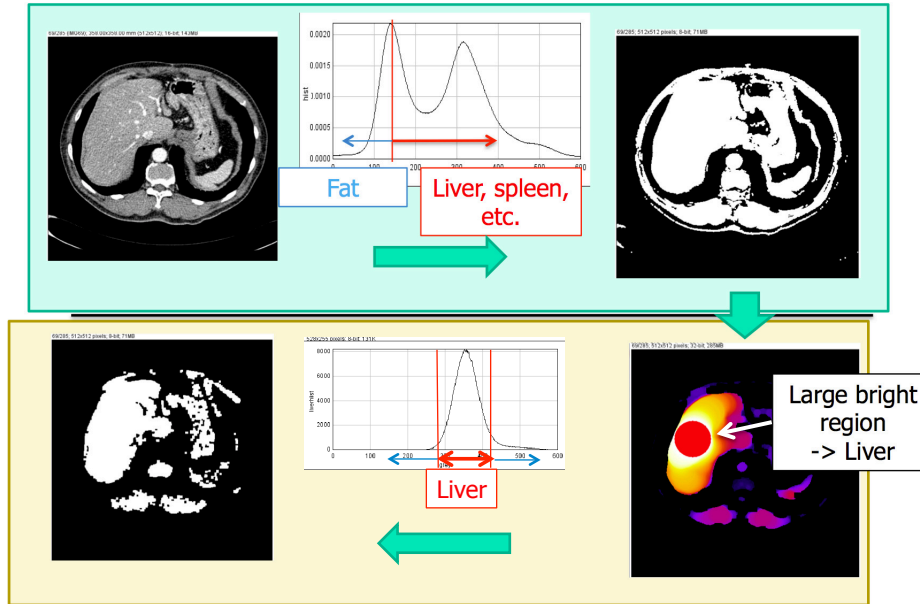
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Fig. 2: Flow of extracting the liver candidate regions based on the intensity model.

2.2 Segmentation based on a shape model

The most outstanding shape feature of the liver is that the liver surface is smoothly rounded and the liver is thick. In order to measure the roundness and thickness at the same time, the local thickness is used. The 3D image(the result of Section 2.1) is segmented as follows. The local thickness values for all point in 3D image are computed as shown the left part in 3. The local thickness image is segmented using Watershed method[7], where the point with the maximum value is used as the seeds, and the point with minimum value is used as watershed points. the Watershed algorithm separates the different organs well since the local thickness tends to be minimum at the boundary points where different organs touches. Figure 3 shows an example of the watershed-based segmentation, where the local-thickness image is segmented into three regions(two regions of the liver and one region of the spleen). Although the Watershed algorithm might segment the local-thickness image into a lot of small regions, appropriate regions are picked up to be merged into a liver region by the process described in the next section.
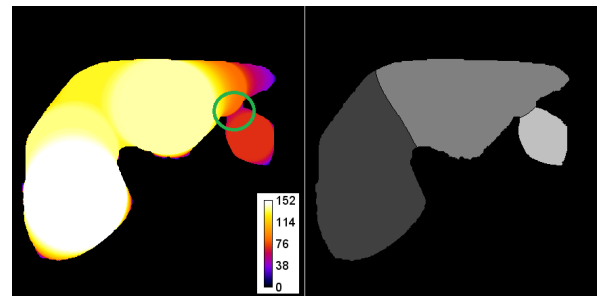
2.3 Merging the segmented regions based on a vessel model

In a liver, there are three types of vessels: hepatic vein, portal vein, and hepatic artery as shown in Fig. 4. Based on this observation, the segmented regions in the previous process are merged into a single liver region by using the vessel information. If a segmented region touches the vessels, it is picked up for a liver region. The vessel data is obtained by using a vessel extraction program developed by
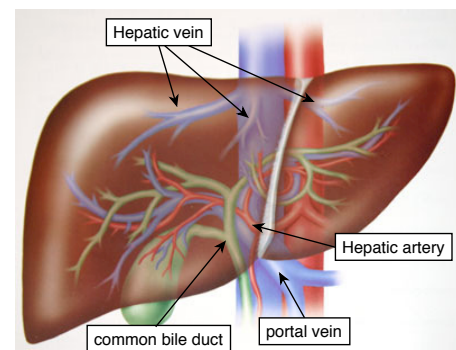

Fig. 3: Segmentation using a shape model.

Fig. 4: Vascular system of the liver.

Hariyama et al.; it extracts the vessels based on line filter[8] and refines the extraction result based on structural analysis. Figure 5 shows an example of this merging process.
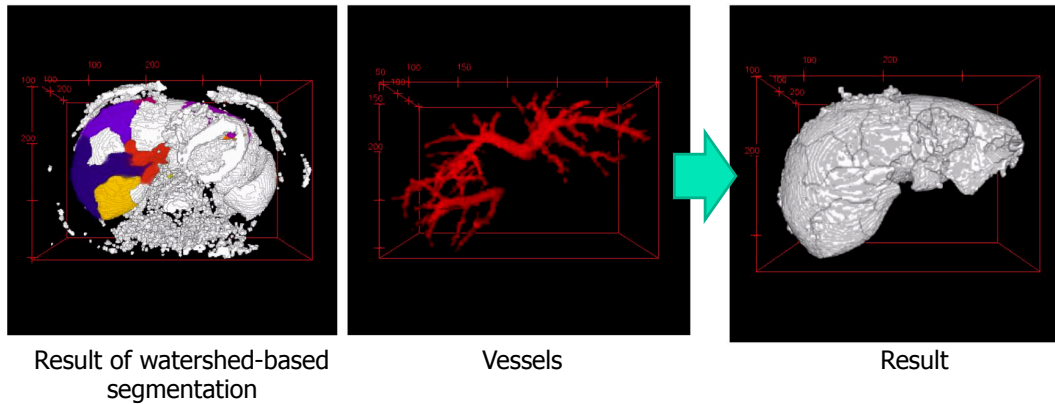
Result of watershed-based segmentation   Vessels   Result

Fig. 5: Merging the segmented regions using a vessel model.
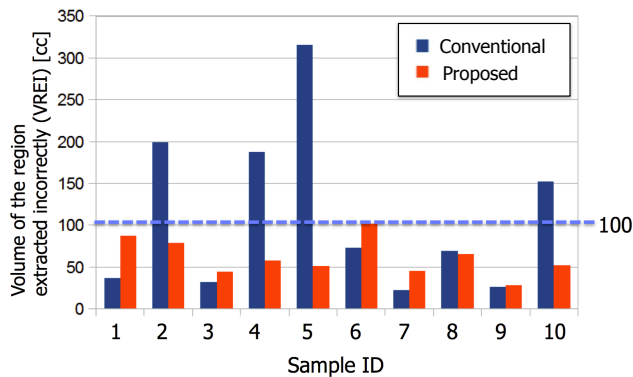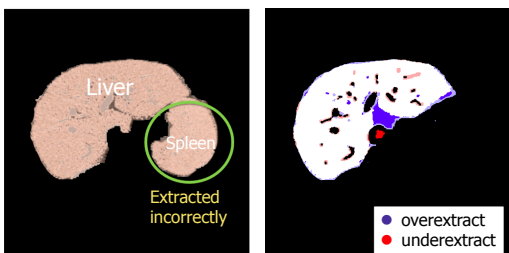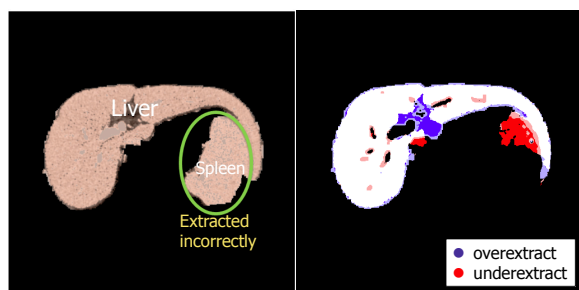

Fig. 6: Comparisons with the conventional method for 10 samples.

(a) Conventional   (b) Proposed

Fig. 7: Improvement in sample 4.

(a) Conventional   (b) Proposed

Fig. 8: Improvement in sample 10.

3. Evaluation

Let us compare the proposed method with a conventional one where the liver region is automatically extracted and not modified manually. As a conventional software, Synapse VINCENT (Fujifilm Medical, Tokyo, Japan)[9] (ver. 2) is used which is one of the widely-used programs for 3D simulation.

The comparisons is done for 10 samples with grand truth which is made manually in terms of the volume of the region extracted incorrectly(called $VREI$ in the following), which is the sum of the volumes of over-extracted and under-extracted volumes. Figure 6 summarizes the comparison results. The average VREIs of the proposed and conventional methods are 61 [cc] and 111 [cc], respectively. The standard deviations of the proposed and conventional methods are 20 and 89, respectively. The proposed method is more robust than the conventional one for change of samples. From some surgeons' experiences, the VREI less than 100 [cc] is desirable for preoperative planning. ;the proposed method can satisfy this requirements. Figures 7 and 8 compares the extracted liver regions for sample 4 and sample 10. In the conventional method, the spleen is extracted incorrectly as the liver since the spleen has a intensity feature similar to the liver. On the other hand, in the proposed method, the spleen is almost removed by exploiting the shape and vessel models.

4. Conclusion

The proposed method can improve the extraction accuracy by combining different types of features. The comparison results demonstrates that the proposed method is more robust for differences of patients. As future work, simultaneous recognition of other organs around the livers is on-going to improve the accuracy.

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