Segmentation and Reconstruction of Abdominal Multi-tissues Based on Multiple Algorithms and Networks

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Abstract. Liver cancer has become a major disease that seriously endangers people's lives and health. In clinical practice, it is necessary to segment the liver, lesions, and other normal organs and tissues in abdominal CT images accurately. However, segmentation of abdominal organs and tissues is a critical and time-consuming process in radiotherapy. Therefore, it is very important to use fully automated and high-precision methods to segment and reconstruct abdominal multi-tissues. This article integrates the automatic recognition process and main segmentation algorithms of skin, bones, intrahepatic blood vessels, liver and lesions. In addition, it supports human-computer interaction to modify the segmentation results, as well as the reconstruction of 3D surface, the measurement of size and volume, and other functions. The threshold segmentation and morphological operations are used in segmentation and reconstruction of skin and bones. And the fuzzy C-means algorithm is utilized in the segmentation and reconstruction of intrahepatic blood vessels. As for the segmentation and reconstruction of liver and lesions, we use convolutional neural network named V-net to accomplish. The experimental results show that the Dice coefficients of the skin and bones segmentation were 98.4% and 92.3%, respectively. The intrahepatic blood vessel segmentation was 78.9%. And the liver and lesions segmentation were 95.4% and 80.4%, respectively. The ensemble algorithm proposed in this paper demonstrated its potential clinical utility in terms of accuracy and time-efficiency.

1. Introduction
The liver is an essential organ for the human body to carry out many critical metabolic activities including synthesizing protein, synthesizing and storing energy substances, decomposing toxic substances in the blood and secreting bile. The liver undertakes many metabolic activities for the human body, which leads to the occurrence of some liver diseases, such as liver cancer. Liver cancer has become a major disease that seriously endangers people's lives and health. And radiotherapy is a significant clinical treatment for liver cancer. The Computed Tomography (CT) image of the human abdomen is an important method for the diagnosis of liver cancer. In the original CT images of liver cancer patients, there are still many other normal organs and tissues besides the liver and lesions. Due to the different tolerances of various organs and tissues to radiation, the impact on other normal organs and tissues must be minimized when radiotherapy is performed on the lesions. And in order to perform radiotherapy more precisely and calculate the dose distribution, the location of the lesions and other normal organs and tissues must be accurately depicted in the CT image. Because manual segmentation is time-consuming, laborious and limited by the physicians, it is necessary to develop new automatic segmentation methods. Although it has attracted widespread attention and research, automatic
segmentation of liver and lesions from CT images is still a difficult task, mainly because of the high
variability of the shape of liver and lesions and the similarity of their intensity to neighbouring areas.
The liver is a soft organ, and its shape highly depends on the adjacent organs and tissues in the
abdomen. In addition, many lesions may cause dramatic changes in the appearance and shape of the
liver, and in many cases, clear edges cannot be seen on many sides of the liver.

Numerous literatures show that there are many types of methods for the automatic segmentation of
liver and lesions. We can divide them into two categories, namely traditional methods with no deep
learning involved and deep learning methods. Traditional methods can be further divided into seven
sub-categories, namely, grayscale based methods (based on histogram[1], based on threshold[2], and
based on clustering[3]), graph cut based methods[4], region growing based methods[5], probability
map based methods[6], statistical shape model based methods[7], level set based methods[8], active
contour model based methods[9]. Deep learning methods can be further divided into 2D methods and
3D methods. In recent years, deep learning methods have made great achievements in the field of
medical imaging. For the automatic segmentation of liver and lesions, deep learning methods have
also achieved higher accuracy and efficiency. Among them, the more famous ones are U-net[10] in 2D
methods and V-net[11] in 3D methods.

This article aims to segment and reconstruct abdominal multi-tissues, and the most important ones
are liver and lesions. This article integrates the threshold segmentation of skin and bones, the fuzzy C-
means (FCM) clustering of intrahepatic blood vessels, and the V-net model of liver and lesions. It is
worth noting that this article supports human-computer interaction to modify the segmentation results,
as well as the reconstruction of 3D surface, the measurement of size and volume, and other functions.

2. Materials and Methods

2.1. Dataset

Two public datasets of liver and lesions segmentation are utilized in our experiment, namely the 3D-IRCADb and LiTS 2017. Among them, the 3D-IRCADb is applied in the segmentation and
reconstruction of skin and bones, intrahepatic blood vessels, and liver and lesions, while the LiTS 2017 is only applied in the liver and lesions. The two data sets are briefly introduced below.

3D-IRCADb: 3D Image Reconstruction for Comparison of Algorithm Database (3D-IRCADb) is a
database that consists of several sets of anonymized medical images of patients, as well as manual
segmentation of various structures of interest by clinical experts. And there are 3D CT scans of 10
women and 10 men with lesions in 75% of cases in 3D-IRCADb. The scanning layer thickness in the
data base is 1.0 mm-4 mm, and the number of liver scanning layers ranges from 74 to 260. The
resolution in every axial slice is 512×512 pixels.

LiTS 2017: Liver Tumor Segmentation Challenge (LiTS) dataset includes 201 contrast-enhanced
3D abdominal CT scans, together with the segmentation labels for liver and lesions regions. 131 scans
had the ground truth labels, and the other 70 scans had not. The scanning layer thickness in the dataset
is 0.8 mm-5 mm, and the number of liver scanning layers ranges from 31 to 301. The resolution in
every axial slice is 512×512 pixels.

2.2. Related Work

2.2.1. Threshold Segmentation. Threshold segmentation is a region-based image segmentation method.
It means divide the image pixels into several categories according to the standard threshold in term of
their intensity, and finally achieve the purpose of image segmentation. The simplest threshold
segmentation is the global threshold segmentation of grayscale images. In practical applications, the
most commonly used threshold segmentation is adaptive threshold segmentation. Adaptive threshold
segmentation can automatically set more reasonable standard thresholds in different regions according
to the different conditions of them, and its final segmentation results are often better than simple
threshold segmentation.
2.2.2. Fuzzy C-Means Clustering. Fuzzy C-means (FCM) clustering algorithm is the most widely used and most successful image segmentation algorithm in all clustering algorithms. FCM divides a collection of \( n \) data points into \( c \) fuzzy clusters, where \( c < n \). Then by minimizing the objective function, usually the sum of squared error (SSE), FCM could find the best locations of these clusters. Hassanien et al.[12] proposed an automated retinal blood vessels segmentation approach based on two levels optimization principles, and FCM is used in the first level to find coarse vessels. Memari et al.[13] proposed a retinal blood vessel segmentation method by using FCM and level sets, in which a genetic algorithm enhanced spatial FCM method is used for extracting an initial blood vessel network.

2.2.3. V-net. Milletari et al.[11] proposed a fully convolutional neural networks named V-net to volumetric medical image segmentation. The main feature of V-net is that it can directly process 3D image data. Since most of the medical data used in clinical practice is 3D data, V-net and its variants have promising application prospects. The middle part of the figure 1 is a schematic representation of V-net. Convolutions are performed to extract features from the data and reduce its resolution with appropriate stride at the end of each stage. The left part of V-net is a compression path, while the right part is used to decompress the signal until it has reached its original size. All convolutions in V-net are applied with appropriate padding.

2.3. Segmentation and Reconstruction of Skin and Bones
A three-stage experimental process of preprocessing, image segmentation and post-processing is proposed for the segmentation and reconstruction of skin and bones. In the preprocessing stage, we first collect the information of the CT scan, then convert the image format, and perform Gaussian filtering. In the image segmentation stage, we use threshold segmentation method to segment the preprocessed image. In the post-processing stage, we first perform the morphological opening operation on the segmented image, then extract the contours and fill the holes, finally remove the baffle imprint of the CT scan to obtain the final result.

2.4. Segmentation and Reconstruction of Intrahepatic Blood Vessels
A three-stage experimental process of preprocessing, image segmentation and post-processing is proposed for the segmentation and reconstruction of intrahepatic blood vessels. In the preprocessing stage, we sequentially perform Gaussian filtering, anisotropic diffusion filtering and local adaptive histogram equalization on CT slices. In the image segmentation stage, we use threshold segmentation method and FCM clustering based on spatial neighbourhood information to segment the preprocessed image. In the post-processing stage, we first perform noise reduction and median filtering on the segmented image, and then execute the region growing algorithm to get the final result.

2.5. Segmentation and Reconstruction of Liver and Lesions
The segmentation and reconstruction of liver and lesions is performed by V-net, which is a volumetric fully convolutional neural network. After end-to-end train on CT volumes of liver, V-net could predict liver and lesions for the whole volume at once. The objective function during training is optimized based on Dice coefficient. Figure 1 briefly describes the process of using V-net to segment liver and lesions.
2.6. Evaluation Metrics

In this section, $|TP|$, $|FP|$, and $|FN|$ are used to represent the true positive, false positive and false negative values, respectively. The Dice coefficient is an approach to determine the spatial overlap between the gold standard image and the segmentation result. The definition of Dice coefficient is shown as follows:[14]:

$$\text{Dice} = \frac{2|TP|}{2|TP| + |FN| + |FP|}$$

The value of Dice ranges from 0 to 1, and 0 represents no overlap, 1 represents complete overlap.

3. Results

3.1. Quantitative Evaluation

The quantitative evaluation results of various organs and tissues are shown in Table 1. As shown in Table 1, the Dice of skin and bones segmentation reached 98.4% and 92.3%, respectively, and the Dice of intrahepatic blood vessels segmentation was only 78.9%. The Dice of liver and lesions segmentation were 95.4% and 80.4%, respectively. Quantitative evaluation showed that the results of skin, bones and liver segmentation were competitive, while the results of intrahepatic blood vessels and liver lesions segmentation were not good enough.

| Category                        | Dice (%) |
|---------------------------------|----------|
| Skin                            | 98.4%    |
| Bones                           | 92.3%    |
| Intrahepatic blood vessels      | 78.9%    |
| Liver                           | 95.4%    |
| Liver Lesions                   | 80.4%    |

3.2. Qualitative Evaluation

3.2.1. Skin and Bones. Figure 2 shows the qualitative evaluation result of a skin segmentation example, and Figure 3 shows the qualitative evaluation result of a bones segmentation example. In Figure 2(b), the overall segmentation results are good, and the general edge information is clearly visible, but in the local texture details, we can see some obvious differences compared with Figure 2(a). In Figure 3(b),
the segmentation of the spine is more successful, and although the skeleton is clear, the bones are generally thinner and some key large bones are missing.

3.2.2. Intrahepatic Blood Vessels. Figure 4 shows the qualitative evaluation result of an example of intrahepatic blood vessels segmentation. In Figure 4(b), although the general blood vessels network is segmented, it is a little fuzzy, and the segmentation results of some blood vessels are coarse.

3.2.3. Liver and Lesions. Figure 5 shows the result of an example of liver and lesions segmentation, where the red area represents the segmented liver, and the green area represents the segmented lesions. Figure 6 shows the visualization result of an example of liver segmentation.
4. Discussion
In this section, we mainly discuss the impact of input image size on Dice in liver segmentation. As shown in Figure 7, when the input image size gradually increases from $128 \times 128 \times 32$ to $256 \times 256 \times 48$, Dice also gradually increases with a larger range. When the input image size continues to increase to $512 \times 512 \times 32$ and $512 \times 512 \times 48$, although Dice has also increased, its increase is smaller than before. In addition, as the input image size gradually increases, the training cost also increases. Considering the model performance and training cost, the final input image size is taken as $256 \times 256 \times 48$, its Dice is 95.4%.
5. Conclusion
For the segmentation and reconstruction of abdominal multi-tissues, this paper integrates various algorithms and networks such as threshold segmentation for skin and bones, FCM clustering for intrahepatic blood vessels, V-net for liver and lesions. The experimental results showed that the Dice of skin and bones segmentation was 98.4% and 92.3%, respectively, and the Dice of liver segmentation was 95.4%. The Dice of intrahepatic blood vessels segmentation was only 78.9%, and the Dice of liver lesions segmentation was 80.4%. It suggests that the results of skin, bones and liver segmentation are promising, while the results of intrahepatic blood vessels and liver lesions are not good enough. In addition, it supports human-computer interaction to modify the segmentation results, as well as the reconstruction of 3D surface, the measurement of size and volume, and other functions. Therefore, human experts can repair and correct the segmentation results through human-computer interaction. With the development of deep learning, it is necessary to develop new network models with higher accuracy and efficiency for intrahepatic blood vessels and liver lesions particularly.

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