Paper:

Automatic Segmentation of Liver Tumor Focus Region Based on CT Image

Mohan Jia[*1], Zhongjian Dai[*1], Zhiyang Jia[*1], and Yaping Dai[*1(✉)]

[*1]Beijing Institute of Technology, No.5 Yard, Zhong Guan Cun South Street,
Haidian District, Beijing, China
E-mail: 929598573@qq.com, padzj@sina.com, Zhiyang.jia@bit.edu.cn, daiyaping@bit.edu.cn

Abstract. In view of the small proportion of liver tumor in abdominal CT images, an automatic segmentation algorithm of liver tumor CT image based on U-net is proposed in this paper. In order to enlarge the size of the target area, image processing was carried out before image input into the segmentation network. And a hybrid loss function combining Dice Loss and Cross Entropy Loss is used to improve the accuracy and stability of the training network. Finally, three evaluation criteria, Dice similarity coefficient, Recall and Precision, are adopted to evaluate the performance of tumor segmentation. The results of experiments show that this method can use less data to complete the end-to-end training and obtain good training effect.

Keywords: Medical Image Segmentation, U-net, Liver Tumor, CT Image

1. INTRODUCTION

According to statistics, liver cancer is one of the most common cancer diseases in the world, which causes a large number of deaths every year[1]. At present, CT and other medical imaging examinations are commonly used to detect tumors. Accurate segmentation of liver tumor is the premise of accurate diagnosis, analysis, and further treatment.

However, most of the clinical diagnosis relies on doctors' manual detection and segmentation, and its accuracy and efficiency completely depend on doctors' clinical experience. This work is not only time-consuming, but also has poor reproducibility. Therefore, many semi-automatic and automatic segmentation algorithms have been proposed.

Massopter et al. [2] first segmented the liver by the active contour technique, and then used the K-means clustering method to extract liver tumors. Vorontsov et al. [3] proposed a semi-automatic liver tumor segmentation method that combined a deformable model with a machine learning mechanism. The semi-automatic segmentation method requires human intervention and still relies on human subjectivity and experience. In recent years, with the rapid development of artificial intelligence and neural network, image segmentation technology based on various neural networks has also been applied to the field of medical image processing. In 2015, Jonathan Long et al. [4] first proposed the Fully Convolutional Networks (FCN) and applied it to image segmentation. It is a milestone in the rapid development of image segmentation research. So far, various liver tumor segmentation methods based on FCN have been proposed, and the segmentation accuracy has been constantly improved.

The automatic segmentation of medical images still faces lots of barriers in practical application. The difficulty of liver tumor segmentation is mainly reflected in the fact that the tumor is complex and variable due to the diversity of individual differences. And it is vulnerable to external interference in the process of medical image imaging. In addition, the scarcity of datasets and the imbalance of samples also make it difficult. We use U-net to automatically detect and segment the focus area of liver tumor in this paper. Before the image is input into the segmentation network, the image processing is carried out to enlarge the size of the target area, and the loss function of Dice Loss and Cross Entropy Loss is used to improve the accuracy and stability of the training network.

2. RELATED WORK

2.1. Fully Convolutional Networks

In 2015, Jonathan Long proposed FCN for image segmentation, and it completed the image segmentation in the semantic level. The biggest difference between FCN and Convolutional Neural Networks (CNN) is that FCN changes the full connection layer to convolution layer at the end of CNN. The input image of the FCN replacing the whole connected layer can be any size, and the output size of the image can be the same as that of the input image. At the same time, it can realize the end-to-end, pixel-to-pixel training and prediction. It also can better consider global information in the segmentation process, and improve the segmentation accuracy. However, the disadvantages of FCN are as follows. First, the segmentation image obtained is not fine enough. Then, the correlation between pixels is not fully considered. At last, spatial consistency is not enough[5].

Ben Cohen et al. [6] used weighted loss function to train Fcn-8s, and used three adjacent slices as input to segment liver regions. Sun et al. [7] used a multi-channel fully convolutional network (MC-FCN) to segment liver tumors. Then they trained one network for each phase of the CT images and fused their high-layer features together.

2.2. U-net

Olaf Ronneberger et al. proposed a new network structure in 2015: U-net [8], which won the ISBI competition champion. After being proposed, it has been widely used in medical image segmentation. The idea of U-net and FCN is very similar, but U-net adopts a completely different feature fusion method from FCN splicing. Unlike FCN's point-by-point addition, U-net combines features together in channel dimension to form thicker features.

Christ et al. [9] adopted U-net for initial liver segmentation, and then optimized the segmentation results by 3D conditional random field. Zhang et al. [10] used U-net for coarse liver segmentation, and then compared the results of refined segmentation according to graph cut based method, level set based method and conditional random field (CRF).

3. CONSTRUCTION OF LIVER SEGMENTATION ALGORITHM

In this study, U-net is used to segment the abdominal CT image. However, in addition to the liver, the abdominal CT image also includes many other organs and tissues, such as the gallbladder, stomach, spleen, kidney, and pancreas. Compared with the whole CT image, the area of the liver tumor is very small. So, it is difficult to segment it. Therefore, the liver is extracted first, and some transformation is carried out to expand the proportion and contrast of the target region. On this basis, the U-net is used to segment the liver tumor. The flow chart of the proposed method is shown in the **Fig. 1**. Each step is described in detail below.

3.1. Image Processing

First of all, the traditional preprocessing operations for the original CT images include pixel value conversion to CT value, windowing operation, histogram equalization, normalization and data enhancement. Then, in order to solve the problem that the small target image is difficult to train, we carry out the following operations on the preprocessed image.

i. The liver mask is used as the mask of the whole abdominal CT image, only the liver region is reserved, and the other parts are set as the background (full black). In this way, we obtain the liver region in the abdominal image and use it as the Region of Interest (RoI) of liver tumor segmentation.

ii. Since the non-RoI area turns black, and the liver tumor is also close to black (the gray value of the tumor is generally lower than that of the liver). So, in order to highlight the tumor part, color reversal is carried out to turn the liver into gray, the tumor into white, and the area outside the liver is black. At the same time, RoI is used to crop the abdominal image and regenerate the liver centered image with specified width and height. This part is used as the input of this stage to segment the tumor in the liver.

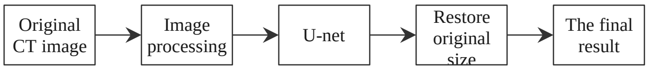
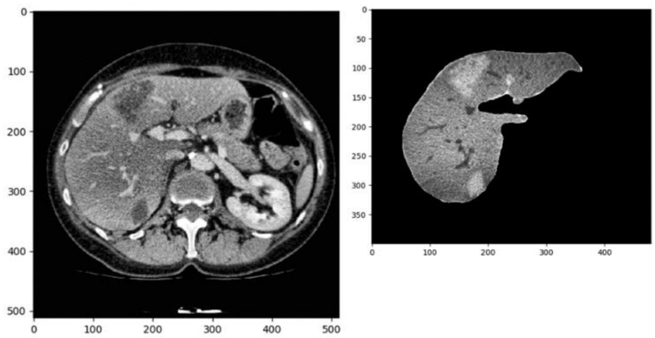


Fig. 1 Flow chart of this method.



Original CT image The processed image

Fig. 2 Comparison chart before and after U-net input.

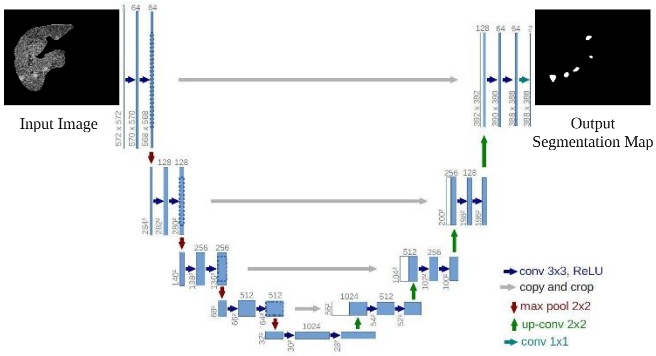


Fig. 3 The structure of U-net.

3.2. The Structure of U-net

The structure of U-net is shown in **Fig. 3**. It looks like a letter U, which is the reason why the U-net got its name. The whole structure is a classical full convolution network. On the left side of the network is a series of down sampling operations composed of convolution and maximum pooling, which is called contracting path. The contracting path consists of four blocks, each of which includes two 3x3 convolutions and a 2x2 max pooling operation. Therefore, the channel depth of the output feature map is doubled and the size is halved.

The right side of the network is called expansive path, which is used for up sampling. This part is also composed of four blocks. Deconvolution doubles the size of the feature map and halves the number of feature channels. Then, it is fused with the feature map with the same depth in the left contracting path. However, it can be seen from the figure that the size of the feature map of the left contracting path and the right expansion path is not the same. Therefore, U-net crops the feature map of the contracting path to the same size as the feature map of the expansive path, and normalizes it. At the end of the network, there is a 1x1 convolution layer, which can map the features of the previous images to the corresponding classification.

3.3. Loss Function

Due to the particularity of medical images, choosing the appropriate loss function can achieve the purpose of accurate segmentation of small targets. Our loss function is

a combination of Cross Entropy Loss and Dice Loss. The dice part of the loss function is beneficial to the sample imbalance in medical image segmentation. But it will have a negative impact on the back propagation, which makes the training unstable. While the cross entropy part can ensure the stability of the training process.
The Dice Loss is as follows:

$$L_{Dice} = 1 - DSC = 1 - \frac{2\times|Seg\cap Ref|}{|Seg|+|Ref|} \tag{1}$$

Seg is the segmentation result of the algorithm, and *Ref* is the result of manual segmentation.
Cross Entropy Loss is as follows:

$$L_{CE} = -(ylog\hat{y} + (1-y)\,log(1-\hat{y})) \tag{2}$$

where $\hat{y}$ is the probability that the model prediction sample is a positive example, and y is the sample label.
The hybrid loss function is as follows:

$$L = L_{Dice} + L_{CE} \tag{3}$$

4. EXPERIMENTS

This section introduces the comparison of experimental results of three different loss functions. The automatic segmentation algorithm is implemented using Tensorflow and Keras framework with Python on Windows10 operating system, and experiments were conducted on a Dell laptop (Intel Core i7, 8GB RAM) equipped with NVIDIA GeForce GTX1650 GPU.

4.1. Data Description

To validate our method, we tested our algorithm on the 3Dircadb dataset[11], i.e. enhanced abdominal CT images in venous phase, and the image format is DICOM. The dataset contains twenty venous phase enhanced abdominal CT images, fifteen of which contain liver tumors. We used the two subfolders under this folder, which are PATIENT_DICOM (original abdominal CT) and MASKS_DICOM (there are split mask diagrams in different parts, such as liver and liver tumor). The resolution of these CT images is 512 × 512. A part of the dataset is shown in **Fig. 4**.

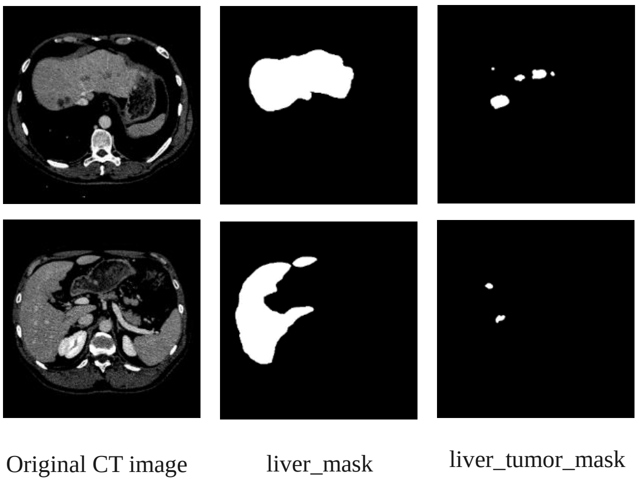


Fig. 4 Partial data in 3Dircadb.

4.2. Experimental results

In this paper, the experimental result of the hybrid loss function of Cross Entropy Loss and Dice Loss is compared with Cross Entropy Loss and Dice Loss.
Dice similarity coefficient(DSC) [12] is used to evaluate tumor segmentation performance, and then Recall and Precision are calculated as auxiliary metrics. The formula is as follows:

$$DSC = \frac{2\times|Seg\cap Ref|}{|Seg|+|Ref|} \times 100\% \tag{4}$$

The closer the DSC value is to 1, the more accurate the tumor segmentation result is; when the DSC value is close to 0, the segmentation result is very poor. And there is no coincidence with the labeled image, tumor detection failure or segmentation error.

$$Recall = \frac{TP}{TP+FN} \times 100\% \tag{5}$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \tag{6}$$

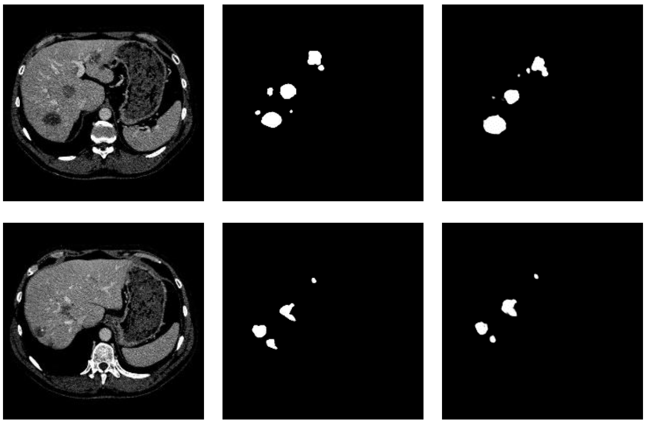
Here, *TP* is true positive; *FN* is false negative; *FP* is false positive. Recall and Precision interact with each other. Generally speaking, if the Precision is low, the Recall will be higher; if Precision is high, the Recall will be lower. Therefore, we should try to make both higher in the actual application process.
Dice Loss is beneficial to the sample imbalance problem, but it will lead to quite unstable training; the stability of Cross Entropy Loss is higher than Dice Loss. But when the number of current scene pixels is far less than the number of background pixels, the performance of Cross Entropy Loss is often not good. And the hybrid loss function combined cross entropy loss function and Dice Loss are used in this paper, which has the advantages of these two loss functions. **Table 1** shows the liver tumor segmentation results with different loss functions. We can see that DICE and Recall with the hybrid loss are better than the other two loss functions. The Precision has little difference with the Cross Entropy Loss. Our loss function performed better in the training process. The experimental results are shown in **Fig. 5**.

5. CONCLUSION

In this paper, U-net is applied to segment liver tumor in CT images. Firstly, the original CT image is processed in order to reduce the image noise and improve image quality. Then the U-net is used to segment the image. Finally, the size of the output image is restored. Experimental results on datasets show that the proposed method can segment tumors from organs with low contrast and improve the accuracy of image segmentation. However, the accuracy of the algorithm needs to be further improved. In future work, we will continue to improve the algorithm to optimize the performance and generalization ability of the algorithm. For example, we will try to consider the normalization of the two terms in Equation (3) before combining them and weight them.

Table. 1 Performance comparison of tumor segmentation results of different loss functions in 3Dircadb.

Method	DICE	Recall	Precision
Dice	0.6772	0.7352	0.6277
CE	0.7052	0.6525	**0.7671**
CE + Dice	**0.7339**	**0.7511**	0.7174



Original CT image   Manual segmentation result   Segmentation results of this paper

Fig. 5 Algorithm results display.

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