Design of the Segmentation Algorithm of HCC Based on the Improved U-net Network

S Zhou\textsuperscript{1}, W Y Li\textsuperscript{1} and R Lin\textsuperscript{2}*

\textsuperscript{1}School of Biomedical Engineering, Xinhua College of Sun Yat-sen University, China
\textsuperscript{2}Division of Interventional Radiology, Department of Radiology, The First Affiliated Hospital, Sun Yat-sen University, China

Email: 593708354@qq.com

Abstract. Computed tomography is an important method for clinical evaluation of the disease status and the therapeutic efficacy of hepatocellular carcinoma (HCC). In order to effectively reduce the workload of artificial segmentation of CT images and to minimize the obvious influence of subjective factors upon the result, a segmentation algorithm based on the improved U-net network and region growing was proposed. Median filtering and adaptive histogram equalization were performed firstly on abdominal CT images with HCC, secondly the CT images were trained by the improved U-net network in which residual structure and depth separable convolutions layer were used, and then region growing was used for capturing edges of CT images. 126 groups of target CT images were selected for analysis, which were divided into training set, verification set and test set according to the ratio of 8: 1: 1, of which the training set was expanded to 800 by image enhancement technology. By comparing the lesion regions extracted with handled consequences manually labelled by clinicians, the sensitivity reached 83.18%, the accuracy 85.25%, and the Dice coefficient 83.05%. The algorithm revealed a good result on the segmentation of CT image with HCC, and could provide support for the evaluation of the treatment efficacy of HCC.

1. Introduction
Hepatocellular carcinoma (HCC) is a highly prevalent disease with insidious onset in China, who now accounts for almost half of the world’s newcases and deaths [1-3]. Computed tomography (CT) examination is an important method to evaluate the condition and curative effect of HCC. CT scan of the liver has a high resolution, with the help of CT images, liver cancer lesions can be separated from the surrounding tissues, providing a reliable basis for clinical diagnosis and treatment and postoperative evaluation. The segmentation results of liver tumors are an important basis for evaluating the progression of primary liver cancer. Clinical segmentation depends on the subjective experience of doctors. The segmentation results of the same image are not completely consistent among different doctors. Even the segmentation results of the same doctor in different periods may be different. The automatic segmentation of CT images with the aid of artificial intelligence technology can guarantee the accuracy and the consistency and repeatability of the segmentation, which is of great clinical significance.

Common algorithms for tumor segmentation are based on non-machine learning or machine learning, the former of which includes regional growth method, watershed algorithm, level set algorithm, and the latter of which includes support vector machines, neural networks, random forests and unsupervised learning and so on [4-6]. Among them, the semi-automatic segmentation method
still needs manual intervention and is susceptible to subjective factors. The traditional machine learning segmentation method is cumbersome and needs higher requirements for the researchers’ experience, because its extraction of image features depends on artificial experiments. The automatic segmentation method based on deep learning, as the current research hotspot, can realize the automatic segmentation of liver cancer [7]. However, it is difficult to segment tumors with uneven density or weak margins. If some algorithms such as the regional growth method is combined to refine the edge of the lesion, the segmentation accuracy can be higher.

2. Methods
CT images obtained in the arterial phase contains more diagnostic and prognostic information [8], so abdominal CT images of patients with primary liver cancer in enhanced arterial phase were selected for study in this paper, which were from division of Interventional Radiology Department of Radiology, the First Affiliated Hospital, Sun Yat-sen University.

2.1. Image Preprocessing Scheme
In order to reduce the influence of noise and enhance the contrast between the liver and the tumor site, median filtering and histogram equalization were used as a preprocessing step. Both the median filter and the mean filter have different smoothing characteristics for noise, but the mean filter will sacrifice the edge sharpness of the image, while the median filter can successfully filter the noise without damaging the edge sharpness of the image, so the median filter of 3x3 was used to remove the noise, and the result is shown in figure 1b.

After median filtering, the noise was significantly reduced, but the junction between the lesion and the liver was not smooth and the contrast was not high enough. Therefore, adaptive histogram equalization was used to enhance the contrast, and the result is shown in figure 1c.

![Figure 1. Results of image preprocessing.](image)

2.2. Improved Algorithm Based on the U-net Neural Network
The U-net network structure is a deformation of the total convolutional neural network, which was proposed by Olaf Ronneberger et al. of the university of fitzburg in 2015, who’s structure is shown in figure 2 [9].

The U-net network consists of a contraction path and an expansion path, the former of which includes two repeated 3x3 convolution kernels, and the maximum pooling is used for down sampling, after what is up-sample in the expansion path. The detail information is restored by combining the information from the lower sampling layer with the information from the upper sampling layer [10, 11].

The U-net structure has been improved in this paper, as shown in table 1. The deep separable convolution structure in MobileNet network was used to replace the ordinary convolution in U-net, and each layer of 3x3 separable convolution was followed by a layer of BN, as the structure of Resblock shown in figure 3 and the structure of Res1block shown in figure 4. In addition, the ReLU was adopted as the activation function, and the MaxPooling was used for the lower sampling, and the
Transposed convolution was carried out in up-sampling, which was described in the table as Upsampling, and the Merge was used for image mosaic.

![Figure 2. The U-net network structure.](image)

**Table 1. Improved U-net structure.**

| The contraction path | The expansion path |
|----------------------|--------------------|
| Resblock1-64         | Upsampling+Merge   |
| MaxPooling           | Resblock6-512      |
| Resblock2-128        | Res1block7-512     |
| MaxPooling           | Upsampling+Merge   |
| Resblock3-256        | Resblock8-256      |
| MaxPooling           | Res1block9-256     |
| Resblock4-512        | Upsampling+Merge   |
| MaxPooling           | Resblock10-128     |
| Res1block5-512       | Res1block11-128    |
|                      | Upsampling+Merge   |
|                      | Resblock12-64      |
|                      | Res1block13-64     |
|                      | Conv14-2           |

2.3. Testing of the Algorithm Based on the Improved U-net Network Structure

A total of 126 groups of abdominal CT images of patients with HCC were obtained in this experiment, which were randomly assigned to the training set, verification set and test set at a ratio of 8:1:1. In order to obtain better training effect and prevent overfitting during model training, 102 groups of training sets was expanded to 800 by using image enhancement technology. The data enhancement methods adopted were as follows: (1) Rotate the image clockwise or counterclockwise; (2) Flip the image left, right, up and down; (3) Zoom in or out of the image. Then, the training of improved U-net neural network model was realized, based on Tensorflow and Keras library of python platform. The configuration parameters of the improved U-net neural network are shown in table 2.

The results of lesion segmentation based on the improved U-net neural network are shown in figure 5. This algorithm could effectively segment the lesion region and reduce the computation and the size of the network model, but the edge of the lesion was not clearly identified, so the region growing was used for capturing edges of CT images after that.
Figure 3. The structure of Resblock.

Figure 4. The structure of Res1block.
Table 2. The parameters of the improved U-net neural network.

| Parameters     | Values       |
|---------------|-------------|
| Iterations    | 50epochs    |
| Study rate    | 0.001       |
| Batch size    | 8           |

Figure 5. The results of lesion segmentation based on the improved U-net neural network.

2.4. Regional Growth Method Used Together for Image Segmentation

In order to make up for the deficiency of the improved U-net neural network, the region growth method was used in the following step to extract the edge of the lesion. The main process was listed below:

Firstly, we selected the region segmented by the improved U-net neural network as the seed points, and then defined the seed points and the pixel points in the 8-neighborhood as the initial growth area marked as S0, next we calculated the pixel grayscale average \( m_0 \) of the initial region and from that calculated the dynamic difference \( D_0 \) according to equation (1).

\[
D_n = ((x_n - m_n - 1)^2 + (x_n - 1 - m_n - 2)^2 + \cdots (x_1 - m_0)^2)^{\frac{1}{2}}
\]

Compared with the density of the surrounding tissues, the tumor tissue appears to be of low density, so the gray threshold of the image has been used as the growth criterion. The threshold range of the new growth point was determined by equation (2). If the gray level of the new growth point meets the threshold range, it will be added into the growth region, otherwise, it will be removed. Iteration was carried out according to the first step, and the values of \( m_n \) and \( D_n \) were calculated every time to determine the threshold range of the new growable pixel points. \( \theta \) in formula 2 is an adjustment factor, the larger the value of which is, the more fully the region grows but with the negative effect of over-segmentation, on the contrary, the smaller the factor value is, the more likely the under-segmentation will occur. It has been verified by many experiments and finally we have got the optimal value of 0.055.

\[
\Omega_n = [m_{n-1} - \theta D_{n-1}, m_{n-1} + \theta D_{n-1}]
\]

The region stops growing until the area of the nth growth \( (S_n) \) no longer expands. Finally, the segmentation image was filled with holes by morphological closing operation, and the final segmentation image was obtained as shown in figure 6c.
3. Discussion

In order to test the accuracy of the segmentation lesions of the segmentation algorithm, the results were compared with the tumor regions drawn by clinicians on the images. There are some indicators that are commonly used to evaluate the partitioning result such as sensitivity, accuracy, Dice similarity coefficient (DSC), etc. Among them, the sensitivity represents the area ratio between the correct tumor area segmented by computer and the tumor segment sketched by clinicians. The closer the sensitivity value is to 100%, the better the segmentation result is, and the smaller the error rate is. The accuracy represents the area ratio between the tumor area segmented by computer and the tumor segment sketched by the doctor. The closer the accuracy value is to 100%, the better the segmentation result is, and the smaller the probability of the non-focal region being missegmented into the focal region is. DSC is a commonly used similarity measure. The closer the value is to 100%, the higher the coincidence degree between the segmentation result of the algorithm and the clinical division of the lesion is.

The improved U-net algorithm was used to segment the lesions of 12 groups of test set, and the results were compared with the tumor regions manually delineated by the clinicians. The results of sensitivity, accuracy and DSC are shown in Table 3.

Table 3. The results of segment lesions by the improved U-net algorithm.

| Images | Sensitivity (%) | Accuracy (%) | DSC (%) |
|--------|----------------|--------------|---------|
| 1      | 81.63          | 43.48        | 56.74   |
| 2      | 86.79          | 89.13        | 87.95   |
| 3      | 80.04          | 91.15        | 85.23   |
| 4      | 75.81          | 94.58        | 84.17   |
| 5      | 96.61          | 81.48        | 88.40   |
| 6      | 83.44          | 74.24        | 78.57   |
| 7      | 92.66          | 84.51        | 88.40   |
| 8      | 64.34          | 90.71        | 75.28   |
| 9      | 86.39          | 91.29        | 88.77   |
| 10     | 87.65          | 94.94        | 91.15   |
| 11     | 71.67          | 99.50        | 83.32   |
| 12     | 83.48          | 92.18        | 87.61   |
| Average| 82.54          | 85.60        | 82.97   |
The regional growth method was used for edge detail extraction after the improved U-net algorithm, and then the results were compared with the results of the single improved U-net algorithm. The results of sensitivity, accuracy and DSC are shown in table 4.

| Methods                  | Sensitivity (%) | Accuracy (%) | DSC (%) |
|--------------------------|-----------------|--------------|---------|
| The single improved U-net algorithm | 82.54           | 85.60        | 82.97   |
| The fusion algorithm     | 83.18           | 85.25        | 83.05   |

4. Conclusion

Automatic segmentation of liver cancer lesions is of great significance for clinical diagnosis and evaluation of liver cancer progression. We presented a fusion algorithm for segmenting lesions of HCC in this paper, at first the images were trained by the deep learning method based on the improved U-net network to segment the lesion area, and then the edge of the lesion was extracted by region growth method based on gray scale. The result shows that the image has been effectively segmented. From tables 3 and 4, we also found that the result of the fusion algorithm is better than that of the pure deep learning method.

On the basis of the fusion algorithm of liver cancer lesion segmentation, we could extract the lesions of CT images from different periods such as the preoperative, postoperative and second postoperative, and calculate the parameters of active tumor tissue before and after operation. The results of parametric analysis can help clinician to evaluate the postoperative efficacy of hepatocellular carcinoma.

References

[1] Ying Q and Wang Y 2020 China Cancer 29 185-191.
[2] Zhang M Y and Niu J Q 2018 Clin. Hepatol. 34 1399-1402.
[3] Freddie B, Jacques F, Isabelle S, Rebecca L, Lindsey A and Ahmedin 2018 CA: A Cancer Journal for Clinicians 68 394-424.
[4] Sun C J, et al. 2017 Artificial Intelligence in Medicine 83 58-66.
[5] Wang J X, Dou X L and Peter Z 2017 Recent Patents on Computer Science 10 70-79.
[6] Hu P J, Wu F, Peng J L, Liang P and Kong D X 2016 Physics in Medicine and Biology 61 8676-8698.
[7] Yue M Y, Wei Q Y, Deng W, Wang T F, Deng Y and Huang B S 2018 Journal of Biomedical Engineering 35 481-492.
[8] Riccardo L and Josep M L 2010 Seminars in Liver Disease 30 52-60.
[9] Ronneberger O, Fischer P and Brox T 2015 Proc. Int. Conf. on Medical Image Computing and Computer-Assisted Intervention (Cham: Springer) pp 234-241.
[10] Gao H J, Zeng X Y, Pan D and Zheng B 2020 Rectal tumor segmentation method based on improved U-net model Journal of Computer Applications 2020030318.
[11] Sun M J, Xu J, Ma W and Zhang Y D 2018 Chinese Journal of Biomedical Engineering 37 385-393.