SU-UNet: A Novel Self-Updating Network for Hepatic Vessel Segmentation in CT Images

Yang Liu
Academy for Engineering & Technology, Fudan University, China

Xukun Zhang
Academy for Engineering & Technology, Fudan University, China

Haopeng Kuang
Academy for Engineering & Technology, Fudan University, China

Zhongwei Yang
Academy for Engineering & Technology, Fudan University, China

Shichao Yan
Academy for Engineering & Technology, Fudan University, China

Peng Zhai
Academy for Engineering & Technology, Fudan University, China

Lihua Zhang*
Academy for Engineering & Technology, Fudan University, China

ABSTRACT

Hepatectomy is currently one of the most commonly used treatment methods for malignant liver tumors. It is of great significance to clinical surgery to perform accurate hepatic vessel segmentation in preoperative CT images. However, due to the complex structure of hepatic vessels and low contrast in the CT images, it is difficult for experienced doctors to perform accurate manual labeling. Based on this, the labels of the existing public datasets are noisy. In this paper, we propose a double UNet structure based on the soft-constraint method to more accurately segment the vessels from the noisy annotation dataset. First, two different Unet output different segmentation predictions. Then a Self-updating module (SUM) is designed to optimize the noisy vessel label based on segmentation predictions so that the optimized label can better guide the network training. This method can guide the network to get better segmentation predictions. Extensive experiments using a noisy public dataset demonstrate the superiority of our method.

CCS CONCEPTS

• **Computing methodologies**; • **Artificial intelligence**; • **Computer vision**; • **Computer vision problems**; • **Image segmentation**;

KEYWORDS

Medical Image Segmentation, U-net, Noise label, Soft-Constraint

ACM Reference Format:

Yang Liu, Xukun Zhang, Haopeng Kuang, Zhongwei Yang, Shichao Yan, Peng Zhai, and Lihua Zhang. 2022. SU-UNet: A Novel Self-Updating Network for Hepatic Vessel Segmentation in CT Images. In *2022 the 5th International Conference on Image and Graphics Processing (ICIGP 2022), January 07–09, 2022, Beijing, China.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3512388.3512420

*Lihua Zhang is the Corresponding Author.

ICIGP 2022, January 07–09, 2022, Beijing, China

ACM ISBN 978-1-4503-9546-5/22/01…$15.00
https://doi.org/10.1145/3512388.3512420

1 INTRODUCTION

1.1 Background and Challenges of Hepatic Vessels Segmentation

Liver cancer is one of the most common cancers globally, and it is also one of the cancers with the highest mortality rate. Hepatectomy and liver transplantation are currently the most effective treatments for liver cancer. The segmentation of hepatic blood vessels based on computed tomography (CT) images is essential for the preoperative planning of hepatectomy and liver transplantation.

However, due to the complex structure, low contrast, noise, and various pathological changes of hepatic vessels, it is difficult to obtain complete, accurate, and high-quality hepatic vessel annotation data in reality. Most of the currently published datasets are noisy labels. As shown in Figure 1, in clinical practice, hepatic vessels are often under-annotated (Figure 1. Left) or over-annotated (Figure 1. Right). These noisy labels will introduce unavoidable misdirection to the segmentation algorithm.

1.2 The Work of This Paper

This paper proposes a new double UNet [1] structure based on a soft-constraint method for hepatic vessel segmentation. This method uses the noisy labels provided by the dataset as a guide to train two UNet with differences. When the two UNet converge, a new label is generated through a soft-constraint method. Then use the new label to continue training two UNet. This method makes the network output more reliable. The main work of this paper is as follows:

- We use two different UNet structures to output two different segmentation predictions and optimize the noisy label based on the confidence of the prediction;
- A Self-Updating Module (SUM) is proposed to optimize the label to better guide the network training;
- Experiments on the public noisy-labeled hepatic vessel dataset prove the effectiveness of the proposed method.

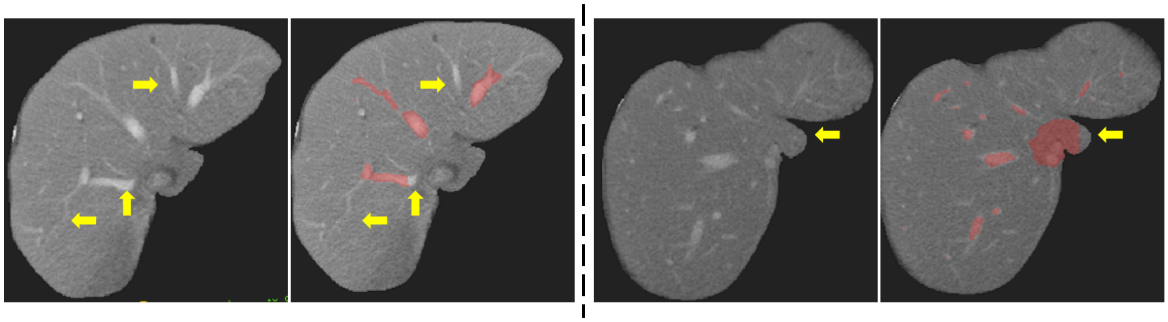

Figure 1: The problem of hepatic vessel labeling in MSD8 [5] dataset. The left side shows the under-annotation in the image, and the right side shows the over-annotation in the image.

2 RELATED WORK

Many algorithms for medical image segmentation have been proposed in the past [2], summarized as traditional methods [3–6] and machine learning methods [7–10]. Previously, Guo et al. [11] combined local and global thresholds to reconstruct cerebrovascular. Hao et al. [12] introduced an area growth algorithm that considers blood vessels' intensity, texture, contrast, shape, and size. Foruzan et al. [13] introduced a blood vessel segmentation method based on a medial-axis enhancement filter. This method first uses various filters to extract high-frequency information and then uses image gradient or multi-scale high-order deviation methods to enhance blood vessels. With the development of deep learning (DL) technology, many researchers began to study DL-based methods in vascular segmentation tasks [14–16] and soon developed it as the dominant method. For example, Ibragimov et al. [17] used CNNs to segment the portal vein in liver CT images. Kehwani et al. [18] presented a multi-task 3D fully convolutional neural network (3D-FCN) for reconstructing the vessel tree. Yan et al. [19] achieved better performance in hepatic vessel segmentation based on deep neural networks. However, the hepatic vessels label has a lot of noise, which makes many current methods still have certain limitations, such as incomplete vascular structure segmentation, blurred vascular boundaries, and sensitivity to image noise.

3 METHODS

Since hepatic vessels only occupy a small part of the pixels in liver CT images, we design a two-stage framework for hepatic vessel segmentation based on a coarse-to-fine strategy. That is first use a network to train and extract the liver region based on the public liver dataset [20, 21], and then segment the blood vessels inside the liver more accurately. The framework of the proposed hepatic vessel segmentation is shown in Figure 2. The first stage is liver area extraction (Figure 2**.** STAGE 1). In the second stage, we proposed a hepatic vessel segmentation framework, namely SU-UNet (Figure 2. STAGE 2). The framework includes two UNet with differences and uses SUM for soft label correction.

3.1 Liver Area Extraction

Since the proportion of hepatic vessels in a complete CT image is small, the usual strategy is to extract the liver area first to reduce the interference of blood vessels outside the liver. Then, the CT image containing only the liver area is used as the input of the following network to segment the hepatic vessels finely. Based on this, we used the public dataset MSD3 with liver labels [22]. We trained a UNet model to perform liver segmentation on abdominal CT images and used the trained model in the blood vessel dataset used in this paper to complete the segmentation of the liver region.

To extract the liver containing the complete vascular structure, we performed an expansion operation on the results of the automated liver segmentation.

3.2 Hepatic Vessels Segmentation Framework

As shown in Figure 1, One of the challenges in the segmentation task of hepatic vessels is that the labels have severe noise. To this end, we propose a loop-optimized hepatic vessels segmentation framework to learn available information from noisy labels. This framework is described in detail as follows.

3.2.1 Learn from Noise Labels. Inspired by ensemble learning, we first input a liver area image into two UNet with differences, namely SE-UNet [23] and Res-UNet [24–26], to obtain different segmentation results. Specifically, SE-UNet combines channel attention and spatial attention to providing more discriminative semantic features. In contrast, Res-UNet has a more effective connection method, improving feature extraction capability. Based on the difference between the two networks, we can get different outputs. Then, we use the noise labels provided by the data set as a guide to training the two different UNet mentioned before until the two UNet converge.

3.2.2 Self-Updating Module. To better use the potential information in the noise label and reduce the erroneous guidance in the noise label, we propose a Self-Updating Module (SUM) based on soft-constraint method. SUM considers combining the segmentation prediction output of the two UNet obtained through 2.2.1 and the noisy hepatic vessel label in the dataset to optimize the hepatic vessel label to be more accurate. Specifically, we generate the confidence of hepatic vessels pixels based on overlapping the segmentation masks obtained by two UNet and label areas, as shown in Figure 3. We consider that the hepatic vessel pixels in the area with the highest overlap of the three labels have the highest confidence. The hepatic vessel pixels in the area with any two labels overlap have the second-highest confidence. The hepatic vessel pixels in a

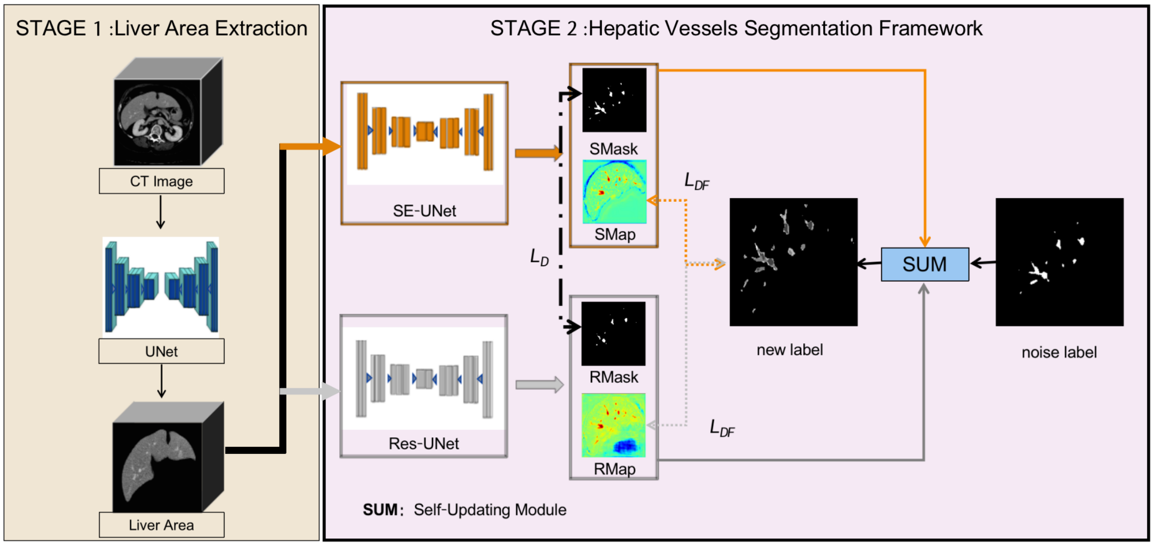

Figure 2: The framework of SU-UNet.

separate area of the noise label have low confidence. The hepatic vessel pixels in a separate area of the segmentation masks obtained by two UNet have the lowest confidence. We will judge the pixels that are considered background by the three labels as background. According to the above order of confidence, we re-adjust the label, the foreground is set to 1, 0.8, 0.6, 0.4, and the background value is 0. Finally, we can get new labels through SUM.

3.2.3 Self-Loop Training. With the proposed SUM, we can construct a self-loop training process. Specifically, we use the new labels obtained through SUM to continue training two UNet that obtained through 2.2.1, and each epoch updates the current labels. After continuous iterations, the network will have more powerful hepatic vessel extraction capabilities.

In addition, as the number of training epochs increases, two models with the same label will involuntarily produce close segmentation predictions. To make the model not fall into the learning bottleneck as mentioned above, we introduce a differential loss function to supervise the prediction of the two models' output to make it have a certain difference.

The loss functions of the two networks used to extract hepatic vessels are:

$$\mathrm{Loss_{DF}} = \mathrm{loss_{dice}} + \mathrm{loss_{focal}} \tag{1}$$

$$\mathrm{Loss} = \mathrm{Loss_{DF}} + \alpha * \mathrm{L_D} \tag{2}$$

where $\mathrm{loss_{dice}}$ denotes the dice loss function used by the two networks, $\mathrm{loss_{focal}}$ denotes the focal loss function used by the two networks. $L_D$denotes the dice score calculated by the two network outputs, which plays a role of regularization that ensures that the output of the two different networks has a certain difference. The parameter α is set to 0.01.

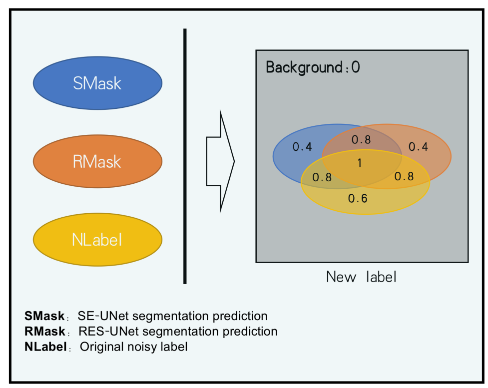

Figure 3: Combine segmentation prediction and noisy labels, update to get new labels.

4 EXPERIMENT RESULTS AND ANALYSIS

4.1 Datasets and Evaluation Metrics

We use the dataset provided by Medical Segmentation Decathlon Task8 (MSD8) [22]. This dataset has 443 CT hepatic scans, including 303 CT hepatic scans with hepatic vessel labels and liver tumor labels. In this dataset, different volumes share the same axial slice size (512 × 512 pixels), while the pixel spacing varies from 0.59 to 0.98 mm, the slice thickness ranges from 1.5 to 7.5 mm, and the slice number is between 26 and 181. During real-world clinical applications, the images were acquired across multiple institutions, anatomies, and modalities. In our experiments, the dataset is randomly divided into 242 cases for training and the remaining 61 cases for testing.

It is worth emphasizing that in this experiment since our method can generate new labels and provide more reliable guidance for the network, our main evaluation metric is to compare visual effects.

Table 1: Results of the different methods. Best results are shown in bold.

Methods	Dice (%) ↑	HD (mm) ↓
UNet [1]	58.38	19.95
TAL [27]	61.90	13.86
Multi-Head [28]	59.49	19.28
Res-UNet [24]	60.18	15.95
SE-UNet [23]	61.29	14.05
SU-UNet(Ours)	62.94	13.31

In addition, to make a quantitative comparison, we calculated two popular metrics, Dice (%) and 95% Hausdorff (mm), for the segmentation mask of the model and the original label to further verify the effectiveness of our method. The calculation of Dice is as follows:

$$\text{Dice} = \frac{2\left|Y \cap \bar{Y}\right|}{\left(|Y| + \left|\bar{Y}\right|\right)} \tag{3}$$

where Y denotes the original labels, $\bar{Y}$ denotes the segmentation masks of the model. The calculation of 95% Hausdorff is as *follows*:

$$H\left(Y, \bar{Y}\right) = \max\left\{\max\left[\min\|y - \bar{y}\|\right], \max\left[\min\|\bar{y} - y\|\right]\right\}, \quad y \in Y, \bar{y} \in \bar{Y} \tag{4}$$

Where $\|\cdot\|$ denotes the distance paradigm of Y and $\bar{Y}$.

4.2 Implementation Details

We have performed data argument (DA) on the input data to expand the diversity of the data. The specific method is as follows: a) simulate different body shapes, scale each CT, randomly increase or decrease the edge of each CT by 0 to 25 pixels; b) to simulate the slightness of a person on a CT scanning device Flip, we randomly flip the CT image clockwise or counterclockwise from 0° to 10°. In addition, we set the HU value of the CT image to a window width of 300 and a window level of 0 to have better image contrast. The intensity of the image is further normalized to be between 0 and 1 for the input of the neural network.

The framework is based on the PyTorch implementation of using an NVIDIA Quatro RTX 6000 GPU. SGD optimizer is adopted, the batch size is set to the number of slices, the learning rate is set to 0.01, the epoch is set to 300.

4.3 Comparison Study

To verify the effectiveness of the hepatic vessel segmentation in our experiment, we have extensively compared our framework, including UNet [1], SE-UNet [23], Res-UNet [24], TAL [27], Multi-Head [28]. The method of TAL and Multi-Head is to design a multi-head network composed of a shared encoder and multiple task-specific decoders. The above methods have achieved good results in hepatic vessel segmentation.

4.3.1 Quantitative Comparison. As shown in Table 1, our method obtains higher values in terms of Dice and HD, which demonstrates the effectiveness of our method. Our method (we selected the network based on SUM to obtain the best performance, SE-UNet + SUM, as the final result of our method) can improve the segmentation performance over the UNet by 4.56%, TAL by 1.04%, and Multi-Head by 3.45% in terms of Dice, reduce the segmentation performance over the Unet by 6.64mm, TAL by 0.55mm and Multi-Head by 5.97mm in terms of HD.

4.3.2 Qualitative Comparison. Since some methods don't have open source code, we mainly compared UNet, Res-UNet, SE-UNet, Res-UNet +SUM, and SE-UNet +SUM. Figure 4 reports the qualitative results. We visualized the original labels provided by the dataset and segmentation mask obtained by the segmentation method mentioned above. Our methods (SU-SEUnet and SU-ResUnet) obtain better performance in visual effects, which once again demonstrates the effectiveness of SUM. Especially for the under-labeled part of the original label, our method proposed in this article can produce better performance than the label and other methods.

4.4 Ablation Study

To validate the effectiveness of the key components proposed in our method, we build a baseline network (SE-UNet) by directly utilizing a cascaded network to segment the hepatic vessel. Then, we add the SUM on SE-UNet, which is denoted as SE-UNet-S. Finally, in the SU-UNet, we introduced a Res-Unet to improve SUM's label update. As shown in Table 2, adding can improve the segmentation performance over the SE-UNet by 0.92% in terms of Dice, and reduce the segmentation performance over the SE-Unet by 0.52mm in terms of HD. At last, when we use two UNet structures and SUM, our method can improve the segmentation performance over the SE-UNet by 1.65% in terms of Dice, and reduce the segmentation performance over the SE-Unet by 0.74mm in terms of HD. The ablation study once again demonstrates the effectiveness of our method.

5 CONCLUSIONS

We propose a method to learn effective information from noisy hepatic vessel labels and iteratively optimize the noisy labels. This method can guide the network to get a better segmentation prediction. Our method uses the idea of ensemble learning, which uses two different UNet to obtain different segmentation predictions. Then, we combine segmentation prediction with original labels to evaluate the pixels' confidence and generate new labels with SUM, providing a more reliable guide to the network. The network will have more effective hepatic vessels segmentation capabilities through iterative training. The experimental results demonstrate the effectiveness of our method. In the future, we will further improve the robustness of our method and apply it to clinical hepatic vessel segmentation.

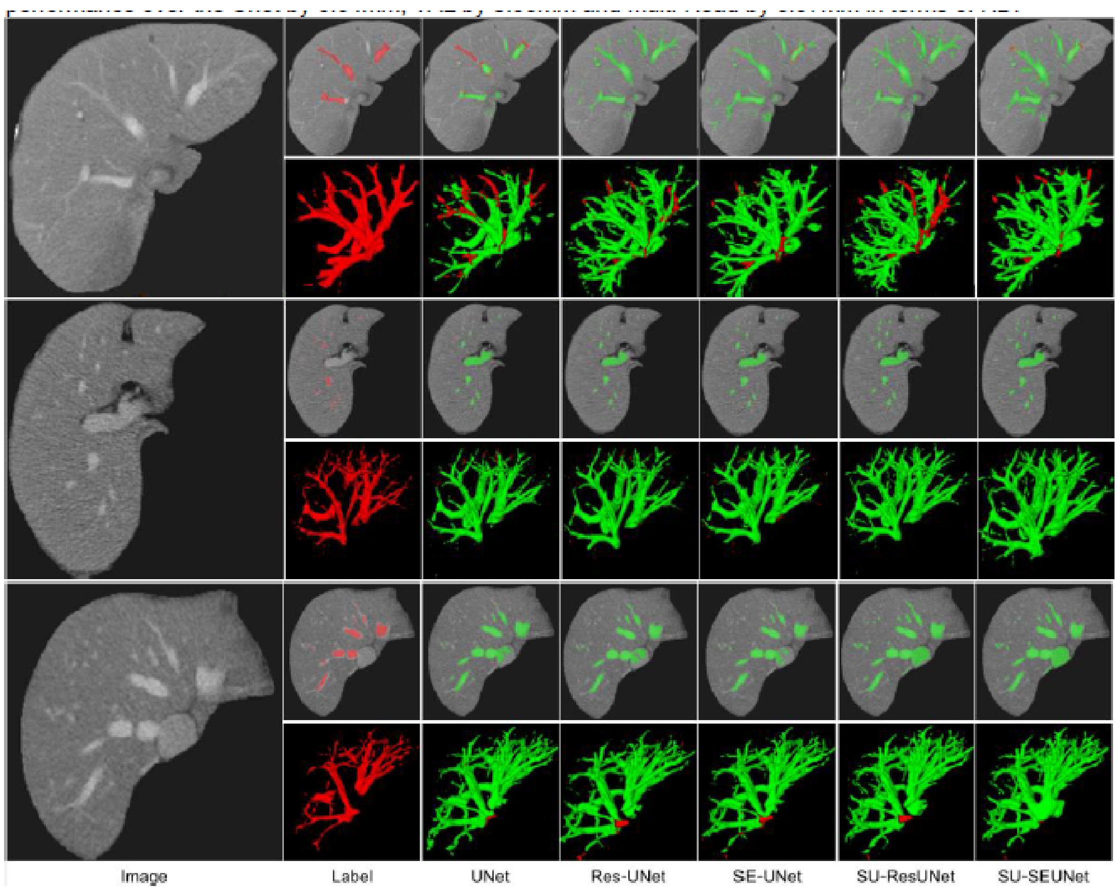

Figure 4: Visualize the 2D and 3D segmentation results obtained by different segmentation methods. The red part represents the label, and the green part represents the prediction obtained after various methods of segmentation.

Table 2: Results of the ablation study. Best results are shown in bold.

Methods	Dice (%) ↑	HD (mm) ↓
SE-UNet [23]	61.29	14.05
SE-UNet-S	62.21	13.53
SU-UNet(Ours)	62.94	13.31

ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China under Grant 82090052, and Shanghai Municipal Science and Technology Major Project 2021SHZDZX0103.

REFERENCES

[1] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. 2015 U-net: Convolutional networks for biomedical image segmentation. International Conference on Medical image computing and computer-assisted intervention. Springer, Cham. https://linkspringer.fenshishang.com/content/pdf/10.1007/978-3-319-24574-4_28.pdf

[2] Khan W. 2013. Image segmentation techniques: A survey. Journal of Image and Graphics, 1(4): 166-170. http://www.joig.net/uploadfile/2013/1226/20131226051740869.pdf

[3] Kaur, Rupinder, and Er Garima Malik. 2014. An image segmentation using improved FCM watershed algorithm and DBMF. Journal of Image and Graphics 2.2 (2014): 106-112. http://www.joig.net/uploadfile/2015/0116/20150116041324133.pdf

[4] Thanammal K K, Vijayalakshmi R R, Arumugaperumal S, *et al.* 2014. Effective Histogram Thresholding Techniques for Natural Images Using Segmentation. Journal of Image and Graphics, 2(2).

[5] Rezaee M, Tavakoli M B. 2014. Cancerous Masses Segmentation by Using Heuristic Ant Colony Algorithms in Medical Images. Journal of Image and Graphics, 2(2): 128. http://www.joig.org/uploadfile/2015/0116/20150116044800406.pdf

[6] Richard, Noël, *et al.* 2013. Fuzzy color image segmentation using watershed transform. 157-160.

[7] Joshua AO, Nelwamondo F V, Mabuza-Hocquet G. 2020. Blood vessel segmentation from fundus images using modified U-Net convolutional neural network. Journal of Image and Graphics, 8(1): 21-25. https://www.researchgate.net/publication/343676765_The_Use_of_Area_Covered_by_Blood_Vessels_in_Fundus_Images_to_Detect_Glaucoma

[8] Otsuki K, Iwamoto Y, Chen YW, *et al.* 2019. Cine-MR Image Segmentation for Assessment of Small Bowel Motility Function Using 3D U-Net. Journal of Image and Graphics, 7(4): 134-139. http://www.joig.org/uploadfile/2019/1113/20191113015618290.pdf

[9] Ono K, Iwamoto Y, Chen YW, *et al.* 2020. Automatic Segmentation of Infant Brain Ventricles with Hydrocephalus in MRI Based on 2.5 D U-Net and Transfer Learning. Journal of Image and Graphics, 8(2): 42-46. http://www.joig.net/uploadfile/2020/0513/20200513110448550.pdf

[10] Wu J, Li G, Lu H, *et al.* 2021. A Supervoxel Classification Based Method for Multi-organ Segmentation from Abdominal CT Images. Journal of Image and Graphics, 9(1). http://www.joig.net/uploadfile/2021/0208/20210208034617900.pdf

[11] Guo J K, Chen C H, Lee J D, *et al.* 1998. 3-D image reconstruction of brain blood vessels from angiograms. Journal of Computers & Mathematics with Applications, 35(8): 79-94. https://sciencedirect.fenshishang.com/science/article/pii/S0898122198000467

[12] Hao, Xiaohui, *et al.* 2000. A novel region growing method for segmenting ultrasound images. IEEE Ultrasonics Symposium. Proceedings. An International Symposium (Cat. No. 00CH37121). IEEE, 2: 1717-1720. https://ieeexploreieee.fenshishang.com/abstract/document/921653

[13] Foruzan A H, Zoroofi R A, Sato Y, *et al.* 2012. A Hessian-based filter for vascular segmentation of noisy hepatic CT scans. International journal of computer assisted radiology and surgery, 7(2): 199-205. https://linkspringer.fenshishang.com/article/10.1007/s11548-011-0640-y

[14] Huang Q, Sun J, Ding H, *et al.* 2018. Robust liver vessel extraction using 3D U-Net with variant dice loss function. Journal of Computers in biology and medicine, 101: 153-162. https://sciencedirect.fenshishang.com/science/article/abs/pii/S0010482518302385

[15] Xu Z, Lu D, Wang Y, *et al.* 2021.Noisy Labels are Treasure: Mean-Teacher-Assisted Confident Learning for Hepatic Vessel Segmentation. https://arxiv.fenshishang.com/pdf/2106.01860.pdf

[16] Ibragimov B, Toesca D, Chang D, *et al.* 2017. Combining deep learning with anatomical analysis for segmentation of the portal vein for liver SBRT planning. Journal of Physics in Medicine & Biology, 62(23): 8943. https://iopscience.iop.org/article/10.1088/1361-6560/aa9262/pdf

[17] Yu W, Fang B, Liu Y, *et al.* 2019. Liver vessels segmentation based on 3d residual U-NET. IEEE International Conference on Image Processing (ICIP). IEEE, 250-254. https://ieeexploreieee.fenshishang.com/abstract/document/8802951/

[18] Keshwani D, Kitamura Y, Li Y. 2018. Computation of total kidney volume from CT images in autosomal dominant polycystic kidney disease using multi-task 3D convolutional neural networks. International Workshop on Machine Learning in Medical Imaging. Springer, Cham, 380-388.

[19] Yan Q, Wang B, Zhang W, *et al.* 2020. An attention-guided deep neural network with multi-scale feature fusion for liver vessel segmentation. IEEE Journal of Biomedical and Health Informatics. https://ieeexploreieee.fenshishang.com/abstract/document/9277536

[20] Borzooie N, Danyali H, Helfroush M S. 2018. Modified Density-Based Data Clustering for Interactive Liver Segmentation. Journal of Image and Graphics, 6(1): 84-87. http://www.joig.org/uploadfile/2018/0717/20180717063433391.pdf

[21] Enokiya Y, Iwamoto Y, Chen YW, *et al.* 2018. Automatic liver segmentation using U-Net with Wasserstein GANs. Journal of Image and Graphics, 7: 94-101. http://www.joig.org/uploadfile/2018/1226/20181226015625255.pdf

[22] Antonelli M, Reinke A, Bakas S, *et al.* 2021. The Medical Segmentation Decathlon. https://arxiv.fenshishang.com/pdf/2106.05735.pdf

[23] Song K, Yang G, Wang Q, *et al.* 2019. Deep Learning Prediction of Incoming Rainfalls: An Operational Service for the City of Beijing China. 2019 International Conference on Data Mining Workshops (ICDMW). IEEE: 180-185. https://ieeexploreieee.fenshishang.com/abstract/document/8955589

[24] Xiao X, Shen L, Luo Z, *et al.* 2018. Weighted Res-UNet for High-Quality Retina Vessel Segmentation. 2018 9th International Conference on Information Technology in Medicine and Education (ITME). IEEE Computer Society. https://ieeexploreieee.fenshishang.com/abstract/document/8589312

[25] He K, Zhang X, Ren S, *et al.* 2016. Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE. https://openaccess.thecvf.com/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf

[26] He K, Zhang X, Ren S, *et al.* 2016. Identity Mappings in Deep Residual Networks. Journal of European Conference on Computer Vision. https://linkspringer.fenshishang.com/chapter/10.1007/978-3-319-46493-0_38

[27] Fang X, Yan P. Multi-organ segmentation over partially labeled datasets with multi-scale feature abstraction. Journal of IEEE Transactions on Medical Imaging, 39(11): 3619-3629. https://arxiv.fenshishang.com/pdf/2001.00208.pdf

[28] Chen S, Ma K, Zheng Y. 2019. Med3d: Transfer learning for 3d medical image analysis. https://arxiv.fenshishang.com/pdf/1904.00625.pdf