A deep learning method for abdomen tissues segmentation in CT images

Zhaoxuan Gong[1],Chong He[1], Yu Liu[1]

[1]shenyang aerospace university
20180008@sau.edu.cn

Abstract.

In this paper, a Convolutional Neural Network (CNN) for automated abdomen tissues segmentation is proposed. In our method, U-net model with attention mechanism is applied to obtain the abdomen tissues. Experimental results show that the proposed method outperforms existing methods. The proposed method is able to provide a precise and robust segmentation estimate, which can also assist the manual abdomen tissues segmentation tasks.

Keywords: abdomen tissues segmentation, attention mechanism, U-net

1. Introduction

The upper abdomen presents a wide spectrum of different medical diagnoses. Correspondingly, the segmentation of the important organs that are located in that area, such as liver, spleen, kidney etc. is an issue physicians are often faced with in clinical routine. Commonly, computed tomography (CT) images are acquired for these purposes. These have the problem that the tissue of different organs are represented with quite similar intensity values in the image data. Additionally, pathologies such as tumors and/or previous resections could alter the organs of the individual patient significantly. In this paper, a deep learning method is proposed for abdomen tissues segmentation, which is based on U-net model with attention mechanism[1].

2. Method

2.1. Preprocessing

None

A detail description of the method used, as chematic representation of the method is recommended.

2.2. ProposedMethod

Figure 1 illustrates the applied attention mechanism on U-Net, where a U-Net [2] architecture is adopted.

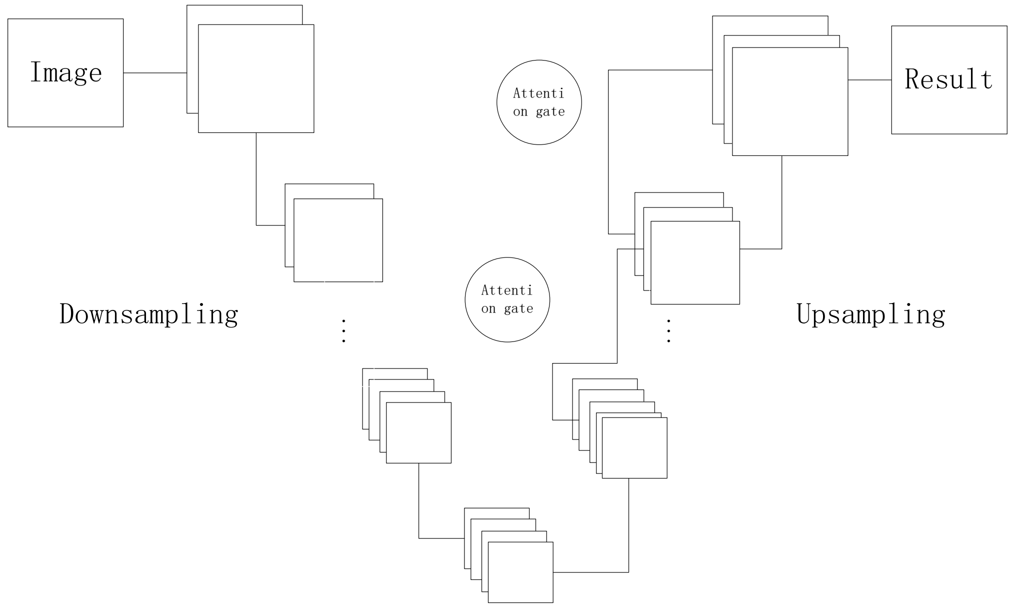

Figure 1. Network architecture

3. Dataset and EvaluationMetrics

3.1. Dataset

- A short description of the datasetused:
  The dataset used of FLARE2021 is adapted fromMSD [4] (Liver [5], Spleen, Pancreas), NIH Pancreas [6,7,8], KiTS [9, 10], and Nanjing University underthelicensepermission.Formoredetailinformationofthedataset,pleaserefertothechallengewebsite and[11].

- Details of training / validation / testingsplits:
  The total number of cases is 511. An approximate 70%/10%/20% train/validation/testing split is employedresultingin361trainingcases,50validation cases, and 100 testing cases. The detail information is presented in Table 1.

Table 1. Data splits of FLARE2021.

Data Split	Center	Phase	#Num.
Training (361 cases)	The National Institutes of Health Clinical Center	portal venous phase	80
	Memorial Sloan Kettering Cancer Center	portal venous phase	281
Validation (50 cases)	Memorial Sloan Kettering Cancer Center	portal venous phase	5
	University of Minnesota	late arterial phase	25
	7 Medical Centers	various phases	20
Testing (100 cases)	Memorial Sloan Kettering Cancer Center	portal venous phase	5
	University of Minnesota	late arterial phase	25
	7 Medical Centers	various phases	20
	Nanjing University	various phases	50

3.2. EvaluationMetrics

- Dice Similarity Coefficient(DSC)

- Normalized Surface Distance(NSD)

- Runningtime
- Maximum used GPU memory (when the inference is stable)

4. ImplementationDetails

4.1. Environments and requirements

A description of the environment used for deployment of themethod,includingbutnotlimitedtotheitemsillustrated in Table2.
The environments and requirements of the baseline method is shown in Table 2.

Table 2. Environments and requirements.

Windows/Ubuntu version	Windows10
CPU	Xeon Silver 4210R 2.4GHz
RAM	64×8GB; 2.4MT/s
GPU	Nvidia RTX 24G
CUDA version	11
Programming language	Python3.6
Deep learning framework	Pytorch (Torch 1.7.0, torchvision 0.9.1)
Specification of dependencies	U-net
(Optional) code is publicly available at	

4.2 Training protocols

Full description of the training protocols, including but not limited to the items illustrated in Table 3.
The training protocols of the baseline method is shown in Table 3.

Table 3. Training protocols.

Data augmentation methods	
Initialization of the network	“he” normal initialization
Patch sampling strategy	More than a third of the samples in a batch contain at least one randomly chosen foreground class which is the same as Unet .
Batch size	8
Patch size	
Total epochs	50
Optimizer	adam
Initial learning rate	0.00001
Learning rate decay schedule	
Stopping criteria,and optimal model selection criteria	Stopping criterion is reaching the maximum number of epoch (50).
Training time	30 hours
CO_2eq[1]	

4.3 Testing protocols

Description of inference strategy to get the final output on test dataset.

Pre-processing steps of the network inputs: The same strategy is applied as training steps.

Post-processing steps of the network outputs: No post-processing step issued.

If using patch-based strategy, describing the patch aggregation method:
None

5. Results

5.2 Quantitative results on validation set

Table 1 illustrates the results on validation cases.

Table 1. Quantitative results on validation set.

Organ	DSC (%)
Liver	93.7
Kidney	93.9
Spleen	87.7
Pancreas	64.4

5.3 Qualitative results

Figure 2 presents some challenging examples. It can be found that the proposed method can segment four tissues accurately.

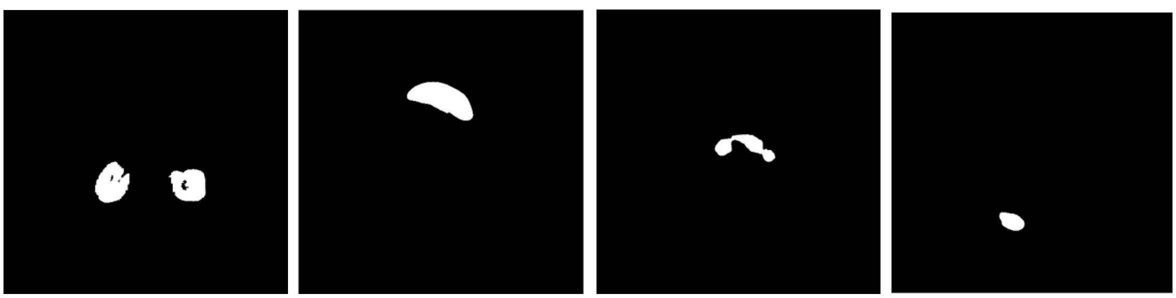

Figure2.Challengingexamples. The predicted results by our method.

6. Discussion andConclusion

In this paper, we proposed a CNN framework for abdomen tissues segmentation. In our method, fractional differential is first used to enhance the contrast of abdomen tissues and its surrounding region. CNN is then designed to produce an initial label of the abdomen tissues region. Finally, maximum connectivity is applied to remove the non- abdomen region. Experiment results show that our method outperforms other method in terms of several evaluation metrics. Some cases received poor segmentation results, especially for pancreas. We believe it can be solved by resize the training images, which is our future work. Our method is general and extendable to other image segmentation problems. We believe that the proposed method will find its utility in more applications in the area of CT segmentation.

Acknowledgment

The authors of this paper declare that the segmentation method they implemented for participation in the FLARE challenge has not used any pre-trained models nor additional datasets other than those provided by the organizers.

References

[1] Multi-object active shape model construction for abdomen segmentation: Preliminary results[J]. Conf Proc IEEE Eng Med Biol Soc, 2012, 2012(4),pp.3990-3993.

[2] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutionalnetworksforbiomedicalimagesegmentation,in*International Conference on Medical image computing and computer-assisted intervention*, 2015, pp. 234–241. 1