Validation and Clinical Application of DL-Based Automatic Target and OAR Segmentation Software, DeepViewer

Z. Peng [1], Y. Chang [1], Y. Li [1], Y. Song [1], H. Wu [2], J. Zhou [4], X. G. Xu [1,3], X. Pei [1]

1 University of Science and Technology of China, Hefei, Anhui 230026, China

2 Anhui Wisdom Technology Company Limited, Hefei, Anhui 238000, China

3 Rensselaer Polytechnic Institute, Troy, NY 12180, USA

4 The First Affiliated Hospital of University of Science and Technology of China, Hefei, Anhui 230001, China

JULY 12–16 2020 VIRTUAL JOINT AAPM | COMP MEETING EASTERN TIME [GMT-4]

INTRODUCTION

Segmentation of organs and tumor target is a key step in radiotherapy, which requires strong knowledge about the anatomical structure. It is often manually finished by the oncologist. But manual segmentation is a labor-intensive and time-consuming process that puts great pressure on oncologists. It is very necessary to develop a tool for auto-segmentation of organs and tumor target.

AIM

To demonstrate the clinical utility of a robust automatic CT segmentation software for radiation treatment planning using deep-learning algorithms.

METHOD

1) CT classification network

- Determining the position of each CT image in human body
- 10 classes along z axis such as brain CT, neck CT and chest CT

2) CT segmentation network [1]

- Segmentation for multiple organs or individual tumor target
- CT value range: [-200, 300], normalizing to [0, 1]
- Training on image patch of 96 x 96 x 96
- Data augmentation: randomly cropping, rotation, and flipping
- Loss function: dice similarity coefficient
- 5-fold cross-validation

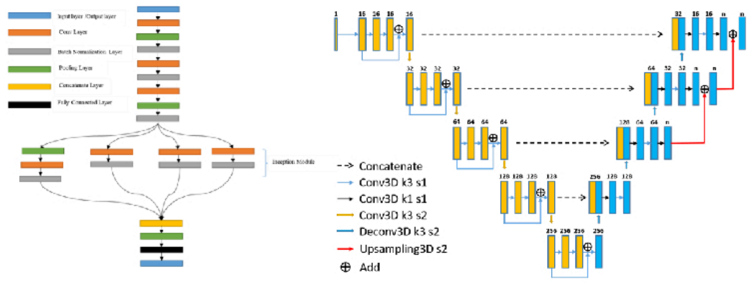


Fig. 1. The structure of CT classification network (left) and segmentation network (right)

RESULTS

1) Datasets:

- Organ: 60 chest patients [2], 43 abdominal patients [3,4]
- Tumor: 50 for esophagus, 80 for breast, 88 for cervical, 79 for nasopharynx (from local hospital)

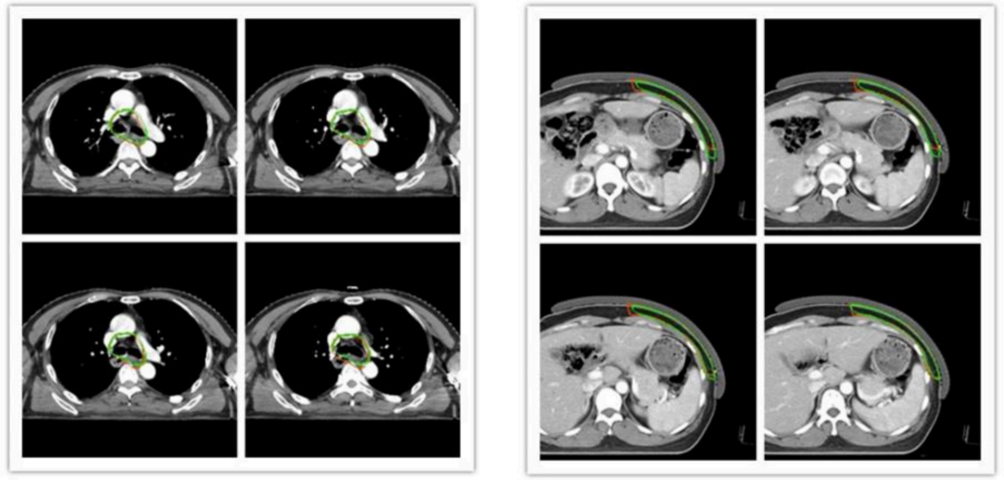
2) The average dice scores for organs and tumor targets are shown in table 1. For cervical tumor target, our dice score (0.86) is higher than trainee doctor (0.83)

3) The visual comparison of segmentation results is shown in Fig. 2 and Fig. 3

4) These models have integrated into segmentation software — DeepViewer, as shown in Fig. 4

Table 1. The Dice Similarity Coefficient for auto-segmentation of organs and tumors

Organ	Dice	Organ	Dice	Organ	Dice	Tumor target	Dice
Right lung	0.96	Esophagus	0.75	Stomach	0.88	Esophagus	0.81
Left lung	0.96	Spleen	0.95	Gall bladder	0.85	Breast	0.84
Heart	0.92	Liver	0.96	Pancreas	0.78	Cervical	0.86
Spinal cord	0.86	Left kidney	0.94	Duodenum	0.60	Nasopharynx	0.82



(red: prediction; green: truth) (red: prediction, green: truth)

Fig. 3. Example of tumor CTV segmentation for esophagus cancer (left) and breast cancer (right).

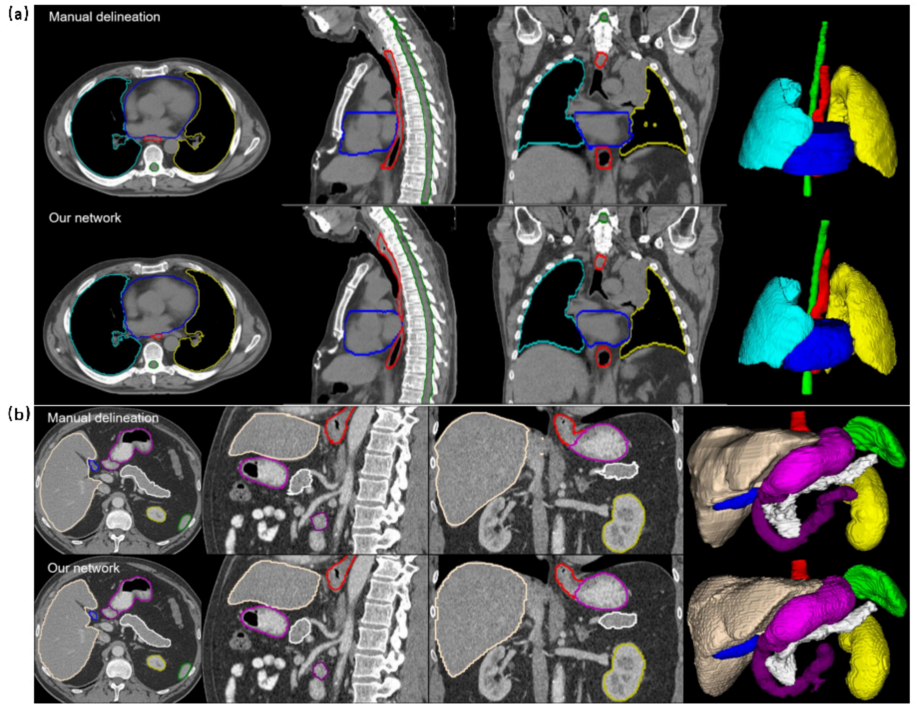


Fig. 2. Examples for visual comparison of organ segmentation between manual methods and our automatic method in terms of axial, sagittal, coronal, and 3D views. (a) left lung (yellow), right lung (cyan), heart (blue), spinal cord (green), and esophagus (red). (b)spleen (green), pancreas (white), left kidney (yellow), gallbladder (blue), esophagus (red), liver (bisque), stomach (magenta), and duodenum (purple).

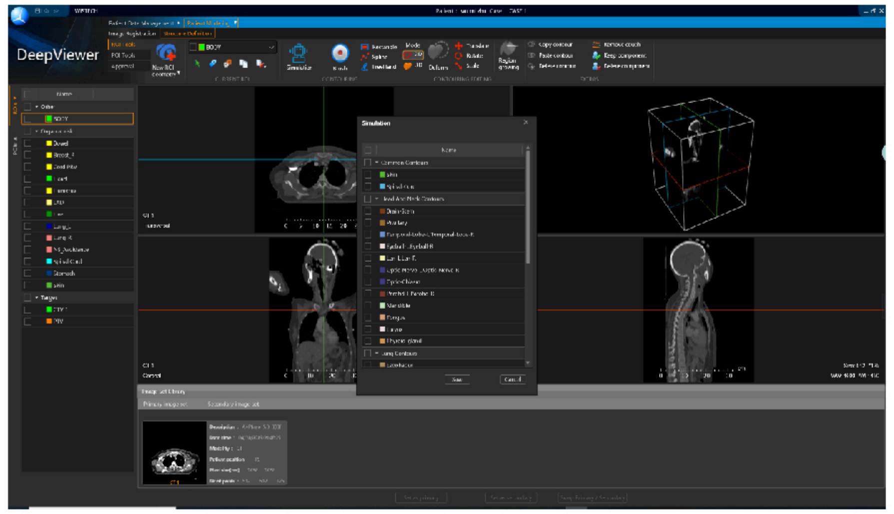


Fig. 4. The GUI of DeepViewer

CONCLUSIONS

- CNN-based automatic segmentation method has achieved good segmentation accuracy in multiple organs and tumor targets
- For some organ such as duodenum or esophagus, the segmentation performance of our network was found to be relatively poor because the organ and its surrounding tissues have similar pixel values in CT image, making the boundary difficult to detect by the CNN model.
- Clinical evaluation of the software has shown excellent accuracy and efficiency as part of the workflow in local busy hospitals.

ACKNOWLEDGEMENTS

This work was supported by National Natural Science Foundation of China (11575180)

REFERENCES

[1] Peng Z, Fang X, Yan P, Shan H, Liu T, Pei X, Wang G, Liu B, Kalra MK, Xu XG. A method of rapid quantification of patient-specific organ doses for CT using deep-learning-based multi-organ segmentation and GPU-accelerated Monte Carlo dose computing. Medical Physics. 2020 Mar 10. (https://doi.org/10.1002/mp.14131)

[2] Yang J, Sharp G, Veeraraghavan H, et al. Data from lung CT segmentation challenge. The Cancer Imaging Archive; 2017.

[3] Roth HR, Farag A, Turkbey E, et al. Data from Pancreas-CT. The cancer imaging archive;2016.

[4] Gibson E, Giganti F, Hu Y, et al. Automatic multi-organ segmentation on abdominal CT with dense v-networks. IEEE transactions on medical imaging. 2018;37(8):1822-1834.

[5] Çiçek Ö, Abdulkadir A, Lienkamp SS, et al. 3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation. International Conference on Medical Image Computing and Computer-Assisted Intervention; 2016.

[6] Dice LR. Measures of the amount of ecologic association between species. Ecology. 1945;26(3):297-302.

CONTACT INFORMATION

Email: hnpz1232@mail.ustc.edu.cn