# Prediction of Three-Dimensional Radiotherapy Optimal Dose Distributions for Lung Cancer Patients with Asymmetric

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## INTRODUCTION

Radiation therapy has been one of the major treatment methods for patients with lung cancer. The balance between the protection of OARs and the efficient and sufficient radiation on PTV requires personalized and well-designed treatment plans. Sophisticated radiation oncologists and dosimetrists may devote more time on iteratively modifying treatment plans through trial and error.

Many researchers has concentrated their efforts to develop automated planning (AP) of radiotherapy. Recently, AP methods are upgrading from traditional knowledge-based method to state-of-the-art data-driven method.

Several researches focus on the prediction based on 2D CT slices, and then the predicted 2D results are stacked to 3D volumes. To utilize the 3D information and improve the prediction accuracy, 3D convolutional neural network (CNN) models are then used.

## AIM

**The iterative design of radiotherapy treatment plans is time-consuming and labor-intensive. In order to provide a guidance to treatment planning, Asymmetric network (A-Net) is proposed to predict the optimal 3D dose distribution for lung cancer patients.**

## METHOD

**A. Patients Data**

392 IMRT treatment plans of lung cancer patients were retrospectively selected. Every treatment plan consists of a series of CT scan, PTV contour, OAR contours, prescription dose, and clinically delivered dose distribution.

**B. Image Preprocessing**

PTV and OARs are filled and encoded to five one-hot masks, and the ground truth is the clinically delivered dose distribution.

**C. A-Net Architecture**

In A-Net, the encoder and decoder are asymmetric, able to preserve input information and to adapt the limitation of GPU memory. Squeeze and excitation (SE) units are used to improve the data-fitting ability.

**D. Loss function**

In order to accurately predict the dose distribution of treatment plans with multiple prescription doses by a single neural network, a new loss function as shown in equation is used.

**E. Evaluation Metrics**

D2, D95, D98, D99, Dmax, CI and HI of PTV were evaluated. V5, V20, MLD of total lung and V30, V40, MHD of heart were evaluated. Dmax of spinal cord were also evaluated. DSC were also analyzed.

## RESULTS

**A. Test results of A-Net**

1) Comparison of Clinical of and Predicted Dose Distribution

As shown in Fig. 1, two cases prescribed with 50Gy and 60Gy were randomly selected from the test dataset for illustration, and the clinical (a and d) and predicted (b and e) dose distribution images, and their voxel-wise difference (c and f) are provided.

Fig. 2 shows the DVH differences between clinical and predicted dose distributions of the corresponding patients in Fig. 1. The solid lines represent the clinical DVH curves of PTV, OARs and Body, while the dashed lines are those drawn from the predicted dose distribution.

2) Statistics of Dose Difference

The Dmean in left lung, right lung, spinal cord, PTV, Body, and total lung are within 2%, and the one in heart is 2.54±2.22%. Dmax in the right lung, heart, PTV, Body and total lung maintain a prediction error under 4%. The largest difference of Dmax was found related to the spinal cord with 6.85±3.95%.

**B. Comparison of Various Networks**

In order to assess the performance and robustness of A-Net, on the same dataset HD-Unet and 3D-Unet were trained and tested. The mean absolute errors between clinical and predicted metrics for PTV and OARs in the test dataset are shown in Table I.

1) Comparison in the dataset combining 50Gy and 60Gy cases

All the errors for the A-Net metrics are lower than at least one neural network, and no metrics for A-Net are worse than both the other two.

2) Single Prescription Dose

Similar as the combined dataset, no errors of any A-Net metrics in both 50Gy and 60Gy datasets are worse than those for both HD-Unet and 3D-Unet.

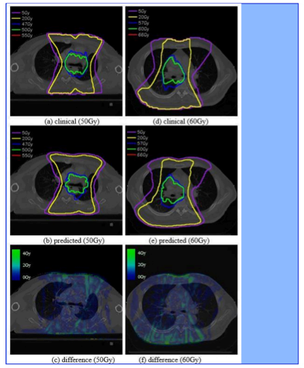


Fig. 1 Comparison of clinical and predict dose distributions of two patients with prescribed 50Gy and 60Gy (the axial slice of each patient was randomly selected in PTV).

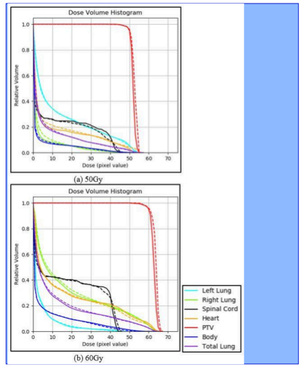


Fig. 2 DVH differences between clinical and predicted dose distributions. Solid lines are from the DVH cures of clinical delivered dose, dashed lines are from prediction.

Table I Mean absolute errors of the prediction of each neural network.

| | A-Net | HD-Unet | 3D-Unet |
|---|---|---|---|
| PTV | | | |
| D95 (% of $D_P$) | 2.64±2.92 | 3.20±3.38 | 3.82±3.71 |
| D98 (% of $D_P$) | 3.21±3.56 | 3.94±3.70 | 4.93±4.68 |
| D99 (% of $D_P$) | 3.65±4.43 | 4.32±4.47 | 5.21±5.26 |
| Dmean (% of $D_P$) | 2.40±2.42 | 2.74±2.54 | 2.66±2.92 |
| CI | 0.04±0.07 | 0.08±0.11 | 0.10±0.15 |
| HI | 0.03±0.03 | 0.04±0.03 | 0.05±0.04 |
| Total Lung | | | |
| V5 (% of volume) | 4.47±3.02 | 4.64±3.18 | 4.17±2.77 |
| V20 (% of volume) | 1.23±1.07 | 1.38±1.11 | 1.55±1.27 |
| MLD (% of $D_P$) | 1.34±1.02 | 1.60±1.01 | 1.21±0.80 |
| Spinal cord | | | |
| Dmax (% of $D_P$) | 7.50±4.74 | 8.42±7.53 | 8.55±6.50 |
| Heart | | | |
| V30(%ofvolume) | 2.70±3.47 | 3.10±3.83 | 3.41±4.98 |
| V40 (% of volume) | 1.68±1.78 | 2.09±2.04 | 1.97±2.18 |
| MHD (% of $D_P$) | 0.02±0.02 | 0.01±0.01 | 0.02±0.02 |

## CONCLUSIONS

**A new network architecture, A-Net, is proposed and developed to predict the dose distribution of treatment plans of lung cancer patients. By using A-Net, the dose distribution is accurately predicted. In future, not only prior knowledge but also the preferences of radiation oncologists could be an improvement to the AI dose prediction model.**

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## REFERENCES

**[1] Batumalai V et al. How important is dosimetrist experience for intensity modulated radiation therapy? A comparative analysis of a head and neck case. *Pract Radiat Oncol 2018; 3(3):* 99-106.**
**[2] Marcello et al. Association between treatment planning and delivery factors and disease progression in prostate cancer radiotherapy: Results from the TROG 03.04 RADAR trial. *Radiother Oncol 2018; 126(2):* 249-256.**
**[3] Moore K-L. Automated radiotherapy treatment planning. Semin Radiat Oncol 2019; 29(3): 209-218.**
**[4] Wei L-Y et al. Integration of deep feature representations and handcrafted features to improve the prediction of N6-methyladenosine sites. *Neurocomputing 2019; 324: 3-9.***
**[5] Ma M et al. Dose distribution prediction in isodose feature-preserving voxelization domain using deep convolutional neural network. *Med Phys 2019; 46: 2978-2987.***
**[6] Nguyen D et al. A feasibility study for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning. *Sci Rep-up 2019; 9(1): 1-10.***
**[7] Chen X-Y et al. A feasibility study on an automated method to generate patient-specific dose distributions for radiotherapy using deep learning. *Med Phys 2019; 46(1): 56-64.***

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