Deep Proton DoseNet: a deep neural network for proton dose distribution image super-resolution

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INTRODUCTION

Proton therapy treatment planning requires accurate high-resolution dose calculation due to well-localized dose deposition property of proton beams compared to photons, which is time-consuming and wastes computational resources. Deep learning is an effective solution to predict high-resolution doses from low-resolution doses accurately and quickly[1].

AIM

This study proposes a novel image super-resolution method for proton dose distributions using a 3-dimensional convolutional neural network (3DCNN).

METHOD

40 head and neck patient CT images with clinical target volume (CTV) contours were collected from the TCIA database[2,3]. These were divided into 90 CT images (30 patients) for training of a CNN model, 15 (5) for validation and testing, respectively. Both 4 mm grid low-resolution (LR) and 1 mm grid high-resolution (HR) dose distributions were calculated so that total 60 Gy-equivalent (GyE) dose was deposited to each CTV volume with 30 fractions from a random beam angle by using an open-source dose calculation toolkit[4]. The LR dose distributions were then upsampled with a scale factor of 4 by trilinear interpolation as baseline reference. A Deep DoseNet-based 3DCNN was also constructed to predict a $200 \times 200 \times 16$ HR dose distribution volume patch by using a set of HR proton stopping power ratio (SPR) volume and LR dose distribution as inputs[5] (Figure 1). 300 epoch end-to-end patch-based training was implemented until mean absolute dose error of the validation data was minimized. For evaluation, the 3DCNN-calculated HR dose distributions of test data were compared with the upsampled LR dose and the actual distributions.

RESULTS

Figure 2 illustrates HR dose distributions calculated by trilinear interpolation and 3DCNN model and their ground truths. Averaged computation time for calculating one 3D dose distribution in test data (with average volume size of $262 \times 263 \times 138$) is 3.7 seconds with a NVIDIA RTX 2080Ti GPU. The trilinear-upsampled dose distributions have large errors especially at lateral penumbra or distal fall-off dose edges. Moreover, the trilinear-upsampled dose underestimated overall doses to patients. In contrast, the 3DCNN-calculated dose represents the true dose accurately. Averaged absolute dose error and its standard deviation over all test data are 1.51 ± 5.33 cGyE for the 3DCNN model whereas 1.97 ± 5.56 cGyE for trilinear interpolation. Relatively elaborated dose errors are yet observed at distal fall-off dose edges.

To evaluate spatial accuracy of 3D dose distributions quantitatively, 3D Dice similarity coefficient (DSC) values between binarized output and true dose distributions with various thresholding dose T were compared between the trilinear-upsampled and 3DCNN-calculated dose (Figure 3). This figure indicates that the 3DCNN-calculated dose distributions are more accurate than trilinear-upsampled dose distributions. Therefore, our proposed method is able to calculate accurate proton dose distributions in 3D volume.

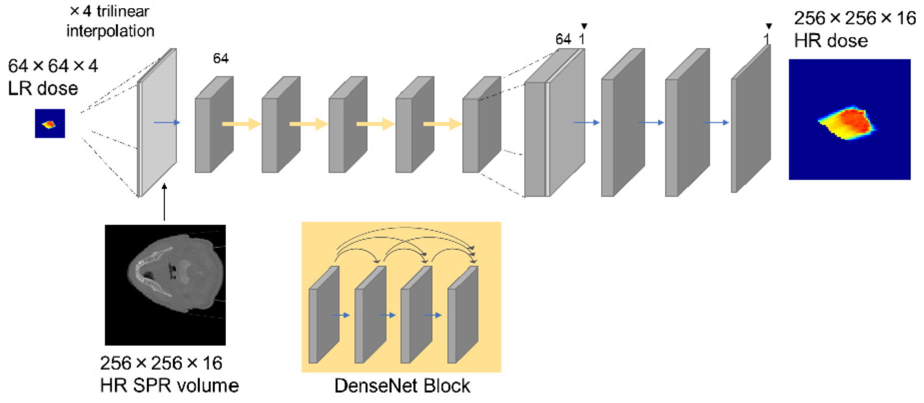

Figure 1. Diagram of neural network architecture. Blue and yellow arrows represent a single 3D convolutional layer and a DenseNet Block with three 3D convolutional layers, respectively. Upsampling was applied with trilinear interpolation.

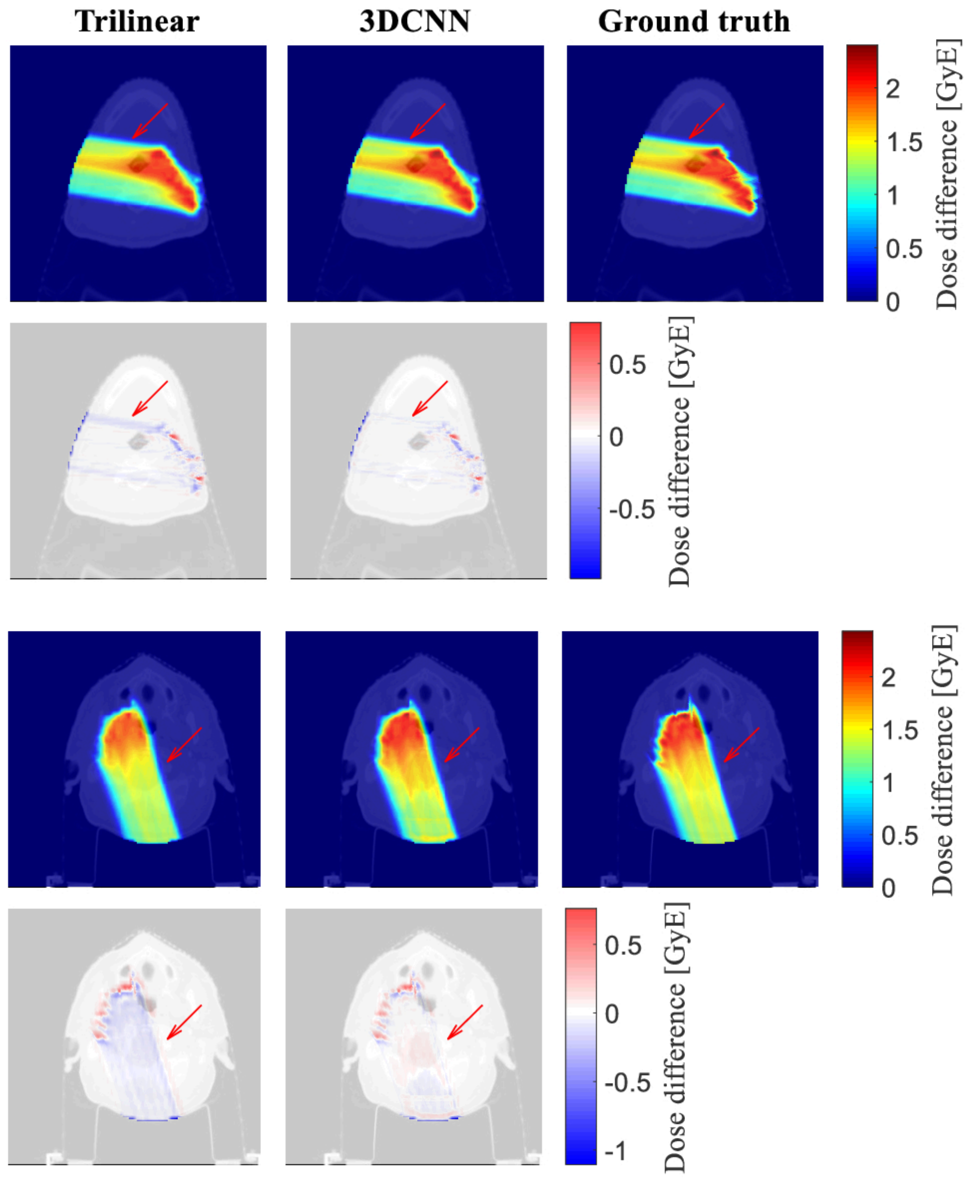

Figure 2. Comparison of dose distirbutions upsampled by two methods (trilinear interpolation and 3DCNN) with ground truths in two axial images. Subtraction doses of trilinear/3DCNN doses from ground truths is also shown.

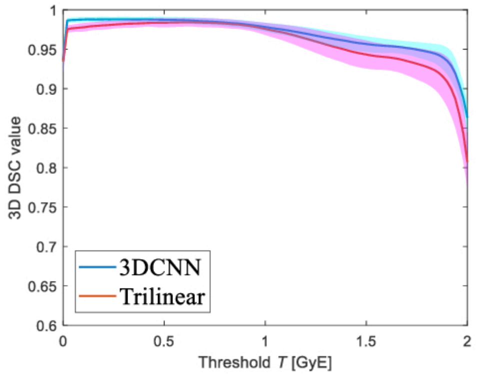

Figure 3. Comparison of upsampled dose distributions with ground truths in two axial slices. Solid lines and bands represent mean and its standard deviation values over all test data, respectively.

CONCLUSIONS

A novel proton dose distribution super-resolution method was established using a 3DCNN. This method calculates high-resolution proton dose distribution from low-resolution dose distribution accurately and quickly. This technique will be useful to evaluate precise deposited dose at small objects from existing treatment plans in retrospective analysis. Moreover, when this method is used in routine proton therapy treatment planning, it will have great potential to accelerate dose calculation time and obtain detailed treatment plans with high spatial accuracy. Elaborating the technique to consider dose error at distal fall-off regions will need to be taken in the future.

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