Convolutional Neural Network Based Sinogram Extrapolation for Truncated CT: Preliminary Study

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Introduction

Truncated computed tomography (CT) is one restriction to increase the quality of radiation treatment planning. Truncation artifact from the small field of view (FOV) degrades the image quality which affects on the accuracy of treatment planning. CT extrapolation using sinogram data have been studied to reduce the truncation artifact from expanding the outside of FOV. In this study, we propose the convolutional neural network (CNN) based sinogram extrapolation as a new method to extend FOV in CT image.

Materials and Methods

I. Network structure

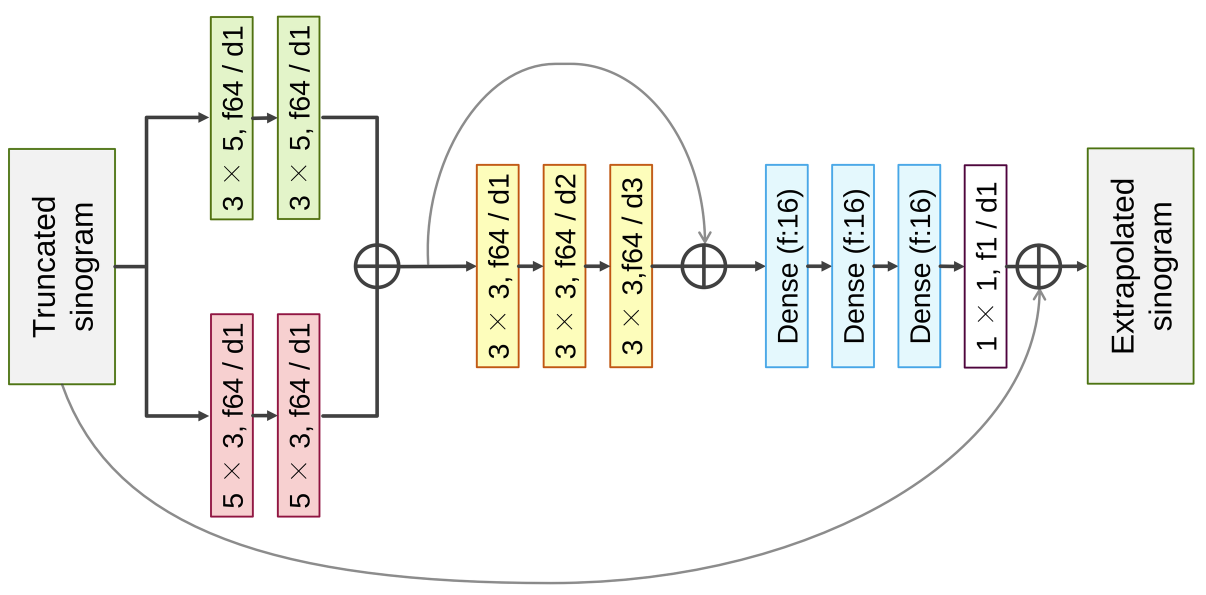

Figure 1. Designed network for sinogram extrapolation. $n \times m$: kernel size, *f*: filter depth, and *d*: dilated factor of convolution layer. Gray line with the sign ⊕ means concatenation.

Figure 1 showed the structure of proposed CNN for sinogram extrapolation. Convolution layers with rectangular kernel 3 × 5 and 5 × 3 were performed for considering the characteristic information from sinogram coordinate. Network structure was not included pooling layer to prevent the data loss resulting from sampling process. Instead of pooling layer, dilated convolution layer was applied to extract the feature from large receptive field. Each dense block repeated four 3 × 3 convolution layer with constant filter depth (f:16), including the feature reuse process. Every convolution layers were followed by batch normalization and relu layer, except the last convolution (1 × 1, f1 / d1).

II. Training Dataset

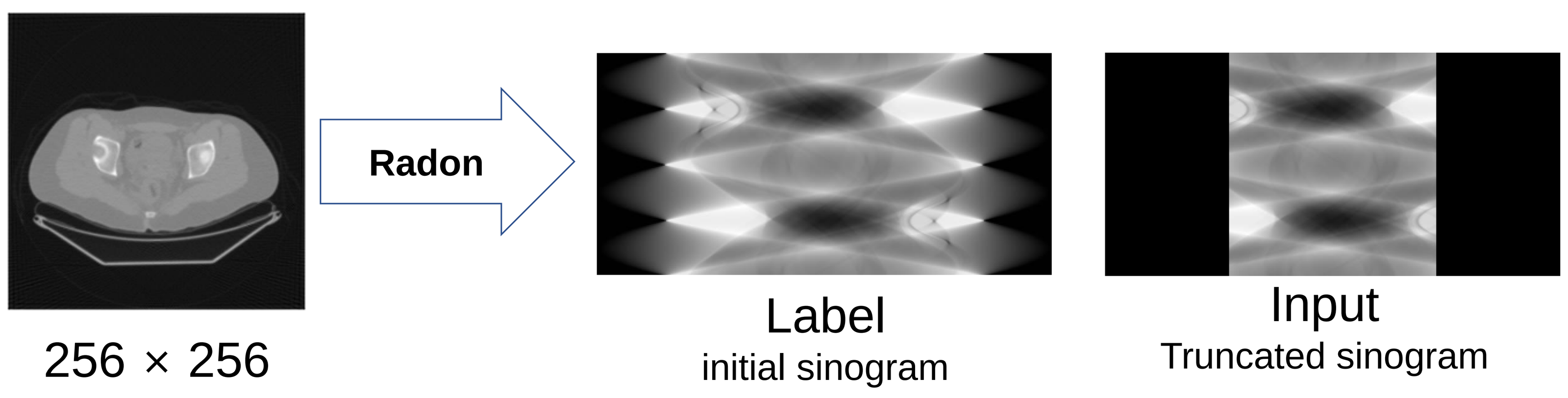

Figure 2. The outline of training dataset. CT slices were converted to 180 view sinogram using MATLAB radon function.

CT dataset was collected from soft-tissue sarcoma dataset from the cancer imaging archive (TCIA). Two thousand of CT slices was randomly selected from 30 patient cases. CT images were converted to sinogram, 180 views in 360º, using radon transform function from MATLAB image processing toolbox. Data range of sinogram were compressed with the integer range 0 to 1023. As the input dataset, a hundred channels at both end of detector axis was erased on the initial sinogram.

III. Training setup

Training loss: mean squared error (MSE)
Optimizer: Adam
Training epochs: 50
Learning rate: 1e-5
Training environment: NVIDIA GTX 1050 (4GB)

Results

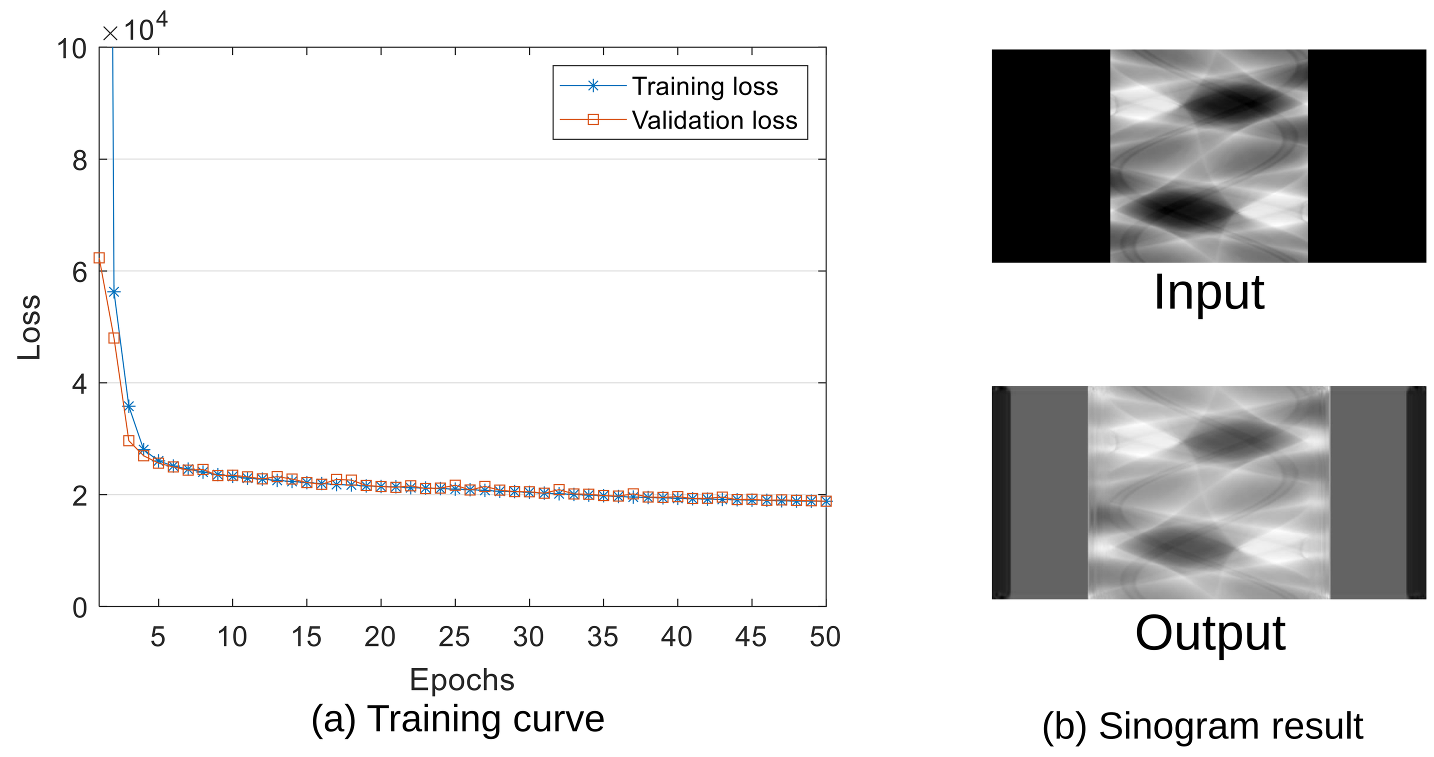

Figure 3. training result of proposed CNN. (a): training curve during 50 epochs. (b) example case of input sinogram (top) and resulted output (bottom).

- No overfitting while 50 epochs
- Trained CNN was extrapolated 19 channels in both side of truncated sinogram
- Extrapolated channel range = summation of dilated factor *d* in convolution layers, excluding 1 × 1 convolution

✓ CT comparison (filtered back projection)

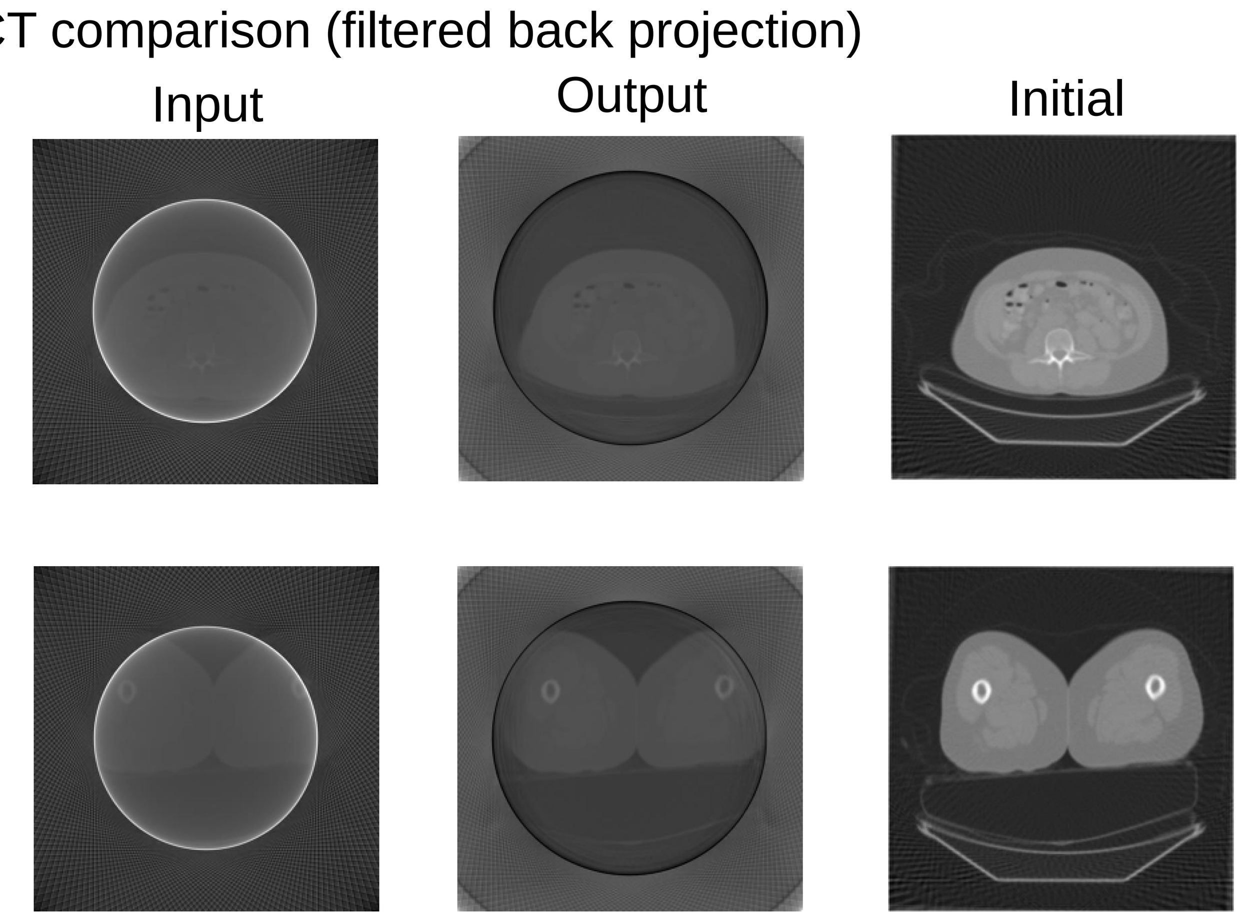

Figure 4. Visual comparison between reconstructed CT images (filtered back projection with Ram-Lak filter).

- Similar body outlines between initial and extrapolated CT
- Structure similarity (SSIM) comparison

SSIM in Sinogram		SSIM in CT	
Initial – Input	0.44	Initial – Input	0.62
Initial - Output	0.81	Initial - Output	0.87

Conclusion

In this study, we proposed the CNN as a new method to extrapolate the truncated sinogram. The proposed CNN structure showed that the FOV in truncated CT can be expanded using deep learning method. CNN was extrapolated only small sinogram channels because the network structure was not fully optimized for sinogram training. Extrapolation results can be upgraded by advanced techniques for CNN training.

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