A Deep-Learning Neural Network based Reconstruction Algorithm for Sparse-View CT

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Abstract

Sparse-view CT image reconstruction is a challenging problem not only due to its ill-posed nature but also due to the lack of a generalizable algorithm. In this work, we developed deep convolutional neural networks to reconstruct sparse-view CT images with CT scans of various sparsity levels. We modified the vanilla U-Net architecture by replacing concatenation in the skip connections with arithmetic addition and replacing bi-linear up-sampling in the decoder with the de-convolution operation. In addition, the max-pool layers in the encoder have been replaced by strided convolutions for down-sampling. Further, we also experimented with such changes as replacing ReLU activations with LeakyReLU in the entire network. Extensive experiments were carried out with simulated as well as real CT scan data by performing an exhaustive hyper-parameter search. Our results demonstrate robust reconstruction performance on Shepp-Logan phantom data as well as the publicly available TCIA data. The network demonstrates satisfactory reconstruction performance with good quantitative image metrics (e.g. RMSE, SSIM, PSNR) for a wide range of sparsity levels.

Introduction

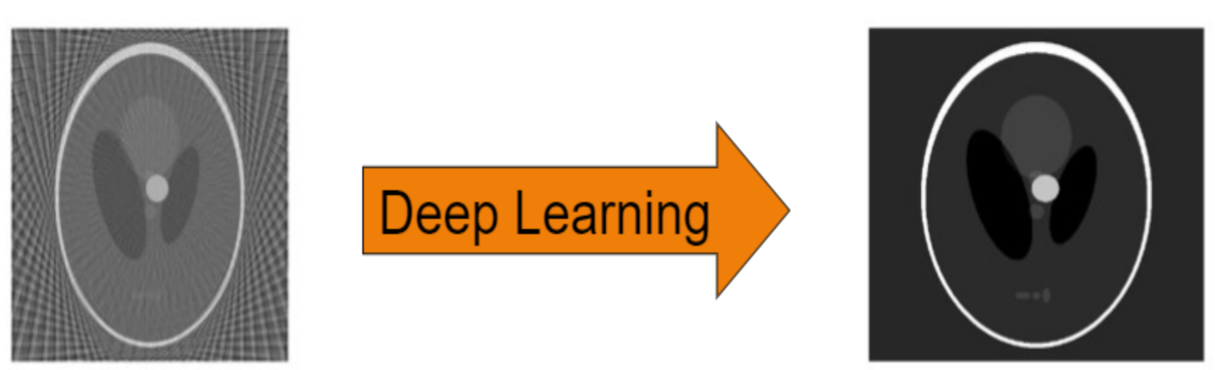

Figure 1. High level workflow of the Deep Learning Neural Network for sparse view reconstruction

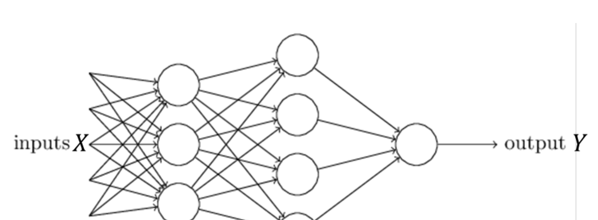

Figure 2. The schematic of deep learning neural network.

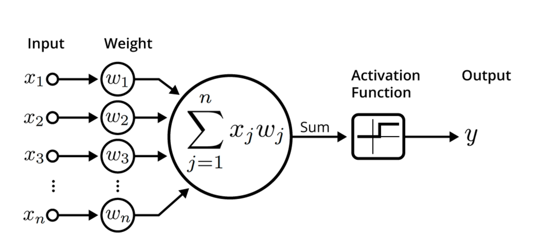

Figure 3. The illustration of an artificial neuron. *(Source: Becoming Human)*

Methods

A DL neural network was constructed from the U-net framework to reconstruct images for sparse-view CT. The DL neural network was trained with data simulated from customized Shepp-Logan phantoms, as well as publicly available CT data at The Cancer Imaging Archive (TCIA). During network training, the network takes each low-quality CT slice image reconstructed by the FBP algorithm as input and reconstructs a full-view equivalent CT image. The image quality of the predicted images was evaluated in terms of RMSE, SSIM, and PSNR.

Methods

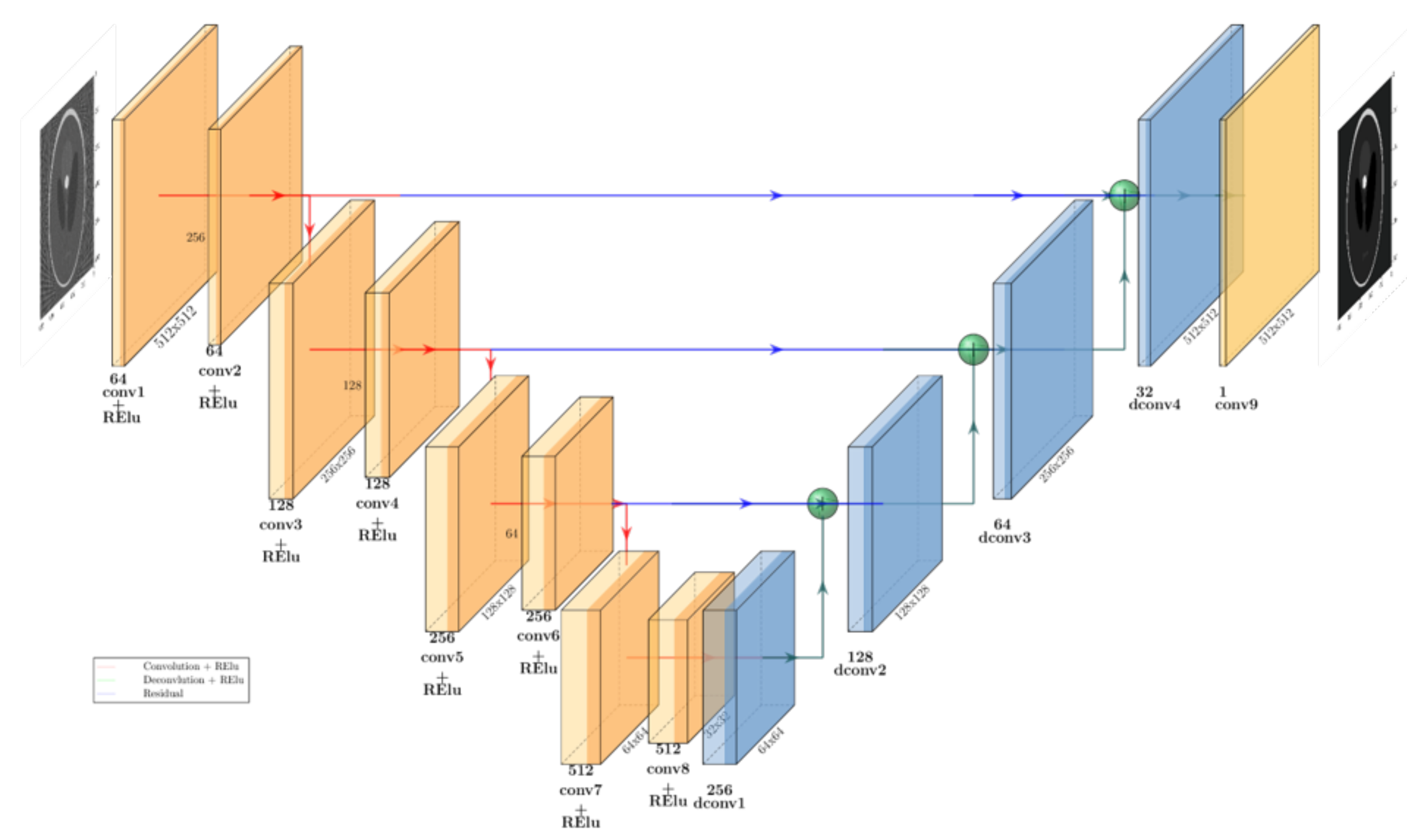

Figure 4. The architecture of the proposed neural network.

Name	Value
Architecture	Modified U-Net Auto-Encoder
Input image size	512x512
Number of layers	13
Number of Convolution layers	9
Number of deconvolution layers	4
Number of Parameters	5,383,809
Cost Function	0.5 * RMSE + 0.5 * SSIM

Table 1. Details of the modified U-Net model

Results

	SSIM	PSNR	RMSE
Deconvolution + ReLU	0.6714	30.8254	0.0044
Deconvolution + LeakyReLU	0.67267	30.6095	0.0046
Bilinear + LeakyReLU	0.6739	30.8687	0.0049

Table 2. The mean values of RMSE, SSIM and PSNR obtained using the TCIA Lung test dataset. 6000 training images used along with 2000 each for validation and testing.

In this section, we present both a qualitative and a quantitative comparison of the results of reconstructing sparse view CT images using the deep neural network described above.

Results

Figure 5 indicates robust qualitative performance of the DL model with significant details captured by the reconstructed image. Table 2 presents quantitative results of two variants of the network architecture. In one case, we replaced all ReLU activations by LeakyReLU, and in another case, we further replaced the all the deconvolution layers by bilinear interpolation .

Figure 5. Qualitative results for a sample in the TCIA data. Left: Original full-view CT image. Center: Sparse CT image with 120 views over 360 degree. Right: Sample reconstructed using our Deep Learning Neural Network.

The results have been obtained by training the neural network model using the TCIA Lung CT data. The model was trained with a total of 10,000 samples with 6000 images for training and 2000 each for testing and validation.

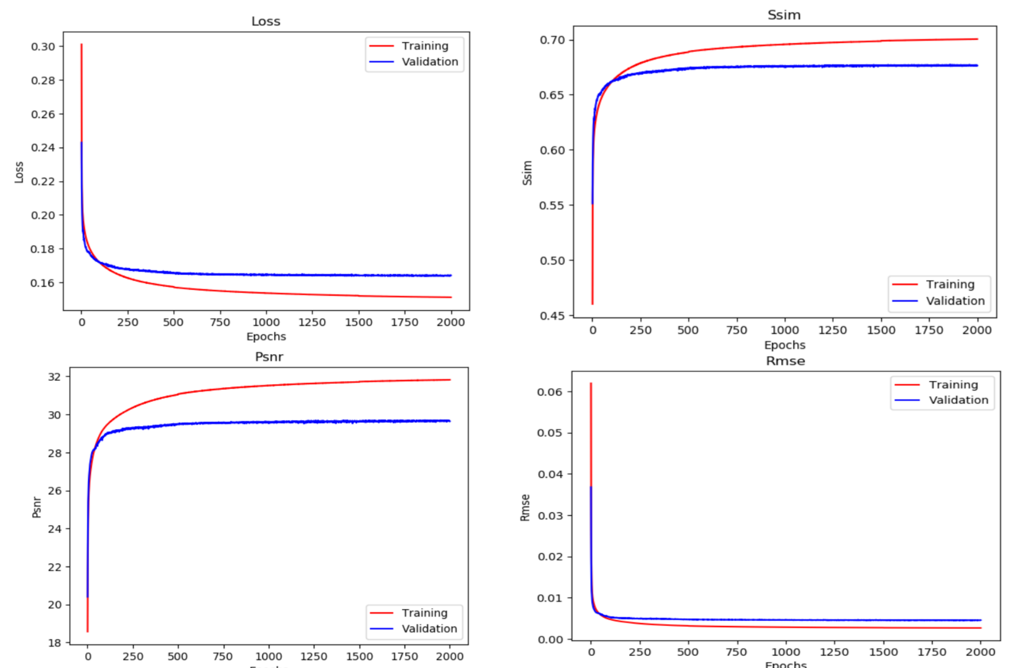

Figure 6. Training-Validation curves. Top row: Custom Loss, SSIM. Bottom row: PSNR, RMSE. Red curve indicates training, blue indicates validation.

Conclusion

In this work, we explored a general modified-U-net based deep neural network to reconstruct sparse view CT images in the image domain. We focus on the effects of network architecture variations and fine tuning on reconstruction performance and present quantitative as well as qualitative results.

References

Zhicheng Zhang, Xiaokun Liang, Xu Dong, Yaoqin Xie, and Guohua Cao, "A Sparse-View CT Reconstruction Method Based on Combination of DenseNet and Deconvolution". IEEE Trans Med Imaging 37(6): p. 1407-1417 (2018).

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