A Deep Learning-Based End-To-End CT Reconstruction Method

K. LU[1,2], L. REN[1,2], and F. F. YIN[1,2]
1Duke University Medical Physics Graduate Program, Durham, NC, USA
2Duke University Department of Radiation Oncology, Durham, NC, USA

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INTRODUCTION

Deep learning is being investigated on CT image reconstruction. A few methods have been proposed to perform post-processing on CT images reconstructed with traditional reconstruction methods to improve image quality[1]. In this study, we propose a deep learning-based end-to-end CT reconstruction method that reconstructs CT images from sonograms. We also compare the performance of the deep learning-based method with traditional CT reconstruction methods on simulated data generated from the Shepp-Logan phantom[2].

AIM

To develop a deep learning-based end-to-end CT reconstruction method and compare it with traditional CT reconstruction methods of filtered-backprojection (FBP) and simultaneous-algebraic-reconstruction-technique (SART).

METHOD

A deep learning-based CT reconstruction method was developed to perform CT reconstruction from X-ray projection data (sinogram). The method contained a deep learning architecture, which incorporated both Convolutional Neural Networks (CNN) with fully connected layer and Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN)[3].

Two-thousand training data (sinogram-slice pairs) with simulated varying internal structures and one test data were generated from Shepp-Logan phantom (128x128 pixels) for 32 and 64 parallel projections spread evenly over 180 degrees. The elliptical structure pointed by the right arrow (Figure 1) was deliberately adjusted so that its long axis stayed in the upper-left to the bottom-right direction. This approach ensured that no sinogram-slice pair in the training set was identical to the testing sinogram-slice pair (Figure 2). The detector size was 128x1 pixels with the source-to-isocenter distance of 750mm and the source-to-detector distance of 120mm.

Three methods (deep learning-based, FBP, and 50 iterations of SART methods) were compared for reconstructing the testing data with the same geometric setup. The performance of the three methods was assessed by comparing the reconstruction speed and quality of the reconstructed images, quantified by peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) index.

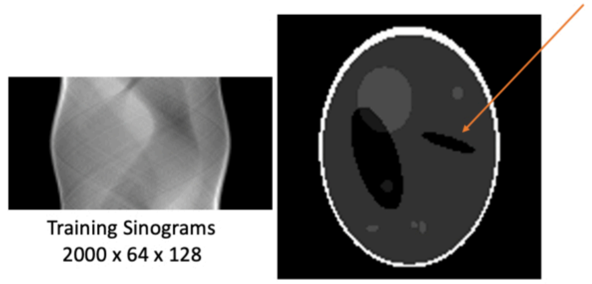

Figure 1: Training Sinograms (64 Proj.) and Slices

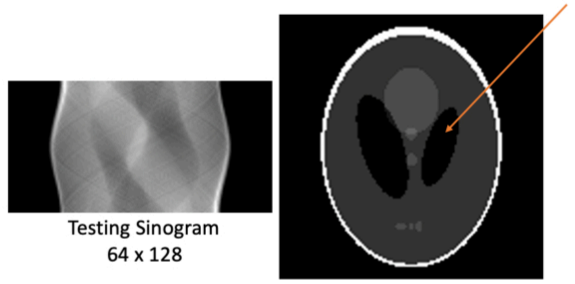

Figure 2: Testing Sinograms (64 Proj.) and Slices

RESULTS

Figure 3 (Figure 4) shows the images reconstructed with the three methods using 32 (64) projections. The image reconstructed with the deep learning-based method has sharper edges around internal structures and fewer artifacts comparing to the FBP and SART reconstructed images. Both the deep learning-based method and the FBP method completed the image reconstruction within 1 second (0.48s for the deep learning-based method and 0.04s for the FBP method using 32 projections; 0.50s and 0.05s respectively for 64 projections), while the SART took 149s for 32 projections, and 223s for 64 projections. PSNR (and SSIM) values of images reconstructed by deep learning-based, FBP, and SART methods were 29.553 (0.977), 11.891 (0.366), and 22.958 (0.918) for 32 projections; 29.120 (0.973), 17.366 (0.467), and 23.571 (0.934) for 64 projections. The values of PSNR, SSIM, and time cost of the three reconstruction methods are listed in Table 1 (Table 2) for 32 (64) projections.

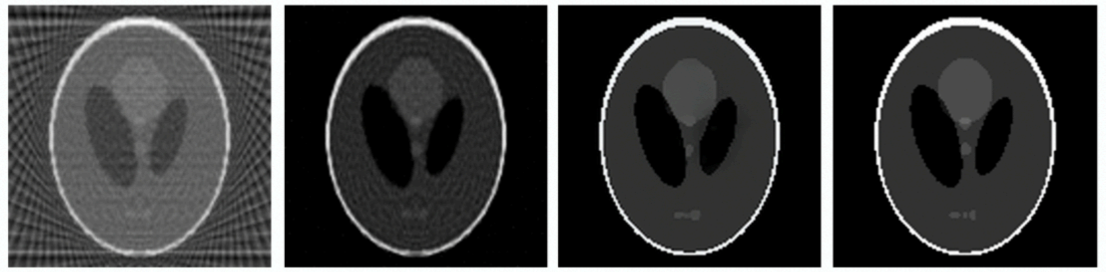

Figure 3: Reconstructed CT Images (32 Projections)

Table 1: PSNR, SSIM, and Time Cost of Three CT Reconstruction Methods (32 Projections)

	PSNR	SSIM	Time Cost
Deep Learning-based Method	29.553	0.977	0.48s
FBP Method	11.891	0.366	0.04s
SART Method	22.958	0.918	149s

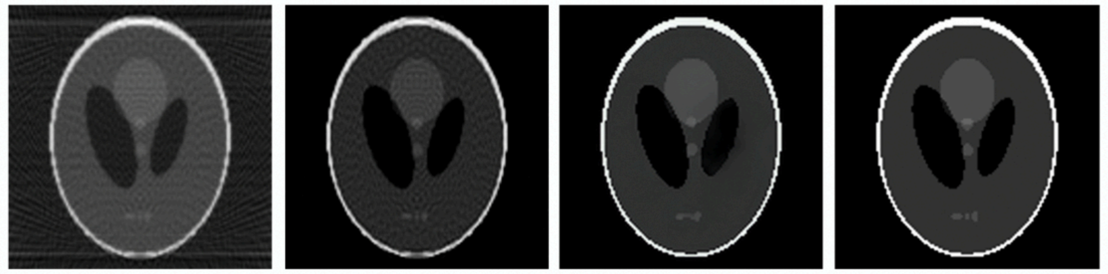

Figure 4: Reconstructed CT Images (64 Projections)

Table 2: PSNR, SSIM, and Time Cost of Three CT Reconstruction Methods (64 Projections)

	PSNR	SSIM	Time Cost
Deep Learning-based Method	29.120	0.973	0.50s
FBP Method	17.366	0.467	0.05s
SART Method	23.571	0.934	223s

CONCLUSIONS

A deep learning-based end-to-end CT reconstruction method that took X-ray projection data (sinogram) as input and generated reconstructed tomographic images as output was developed.

Comparing to the traditional FBP and SART methods, the deep learning-based CT reconstruction method achieved better image quality and fast reconstruction, demonstrating great potential for practical application in real-time high-quality CT image reconstruction.

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CONTACT INFORMATION

Email: ke.lu@duke.edu