Total-Body PET Images Reconstruction Optimization Using Deep Learning

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***Abstract*—The large field of view of Total-body Positron emission tomography (PET) increased the complexity of imaging reconstruction. This study explores the potential of deep learning in the reconstruction of total-body PET. List mode PET raw data were collected for 60 patients from total body PET Siemens Biograph Vision Quadra. The raw data were projected into sinograms. A deep learning reconstruction algorithm based on the VGG network was developed to reconstruct the images from sinograms. The 3D sinograms were constructed into 2D sinogram slides as input of the network. The images reconstructed by the Siemens tool were used as labels, already processed with attenuation correction. There were 644 pairs of data for 1 patient. 60 patients' data were used as a training dataset. The trained network was tested on the other 20 cases. The root-mean-squared error (RRMSE) and structural similarity index (SSIM) were used as a quantitative comparison. The results of the proposed deep learning method showed good performance, specifically less noise, and reveal more details in the region of interest. The RRMSE is 0.76, and the SSIM is close to 1. The preliminary test shows the potential of deep learning in improving the reconstruction of total-body PET, and the attenuation corrections are involved in the network training.**

***Index Terms* — Images Reconstruction, Deep Learning, Total-Body PET**

I. Introduction

THE resolution and signal to noise ratio of reconstructed PET images are limited by various physical degradation factors and low coincident-photon counts detected[1]. Conventional PET image reconstruction methods, for example MLEM, OSEM with iteratively back- and forward-projecting are time-consuming. Usually attenuation corrections are processed to improve image quality, it requires the CT images with additional dose contribution. For Total-body PET, it doesn't require different bed positions to complete a body scanning. The sensitivity is higher compared with normal PET systems, because it has the larger solid angle coverage and longer axial length[2]. Therefore, for the same activity injected in the patient, the total acquisition time can be reduced by a large factor due to the higher sensitivity. With the potential for computational efficiency, deep learning methods have been applied in medical image reconstruction[3]. We can view the deep network as a regularized inverse to the PET system model. It performs as an end-to-end reconstruction process. And the attenuation correction can be involved to achieve low dose reconstruction. Therefore, we proposed a data-driven reconstruction for total-body PET based on deep learning.

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II. Methods

The network we used was modified based on the VGG network[4]. There were 36 convolutional layers of the whole encoder-decoder network, followed by batch normalization layers and rectified linear unit (ReLU) layers, as shown in figure 1.

The input data of the network is sinogram data from Siemens Quadra of 60 patients. The obtained sinograms were 3D data, including 35 segments in one database. In this work, 3D data was rebound to 2D sinograms as the input of the network. It includes 644 2D sinograms for 1 patient. The outputs of the network were reconstructed images. The labels were reconstructed by the Siemens tool, already processed with attenuation correction. They were used as ground truth. For 1 patient, there were 644 reconstructed images.

The loss function is the mean-square error. The optimizer used in this work is the adaptive moment estimation (ADM). The network was trained with a batch size of 22 and 300 epochs. The loss line shows that the training loss approached constant after 200 epochs.

The relative root-mean-squared error (rRMSE), structural similarity index (SSIM), and peak signal-to-noise ratio (PSNR) were used for image quality evaluation.

III. Results

20 patient data were used as test data. Figure 2 showed part of the results, including the input, the ground truth, and the output of the network. It can be seen that the predicted result of the network is primely the same as the ground truth, indicating that this network can achieve the PET image reconstruction

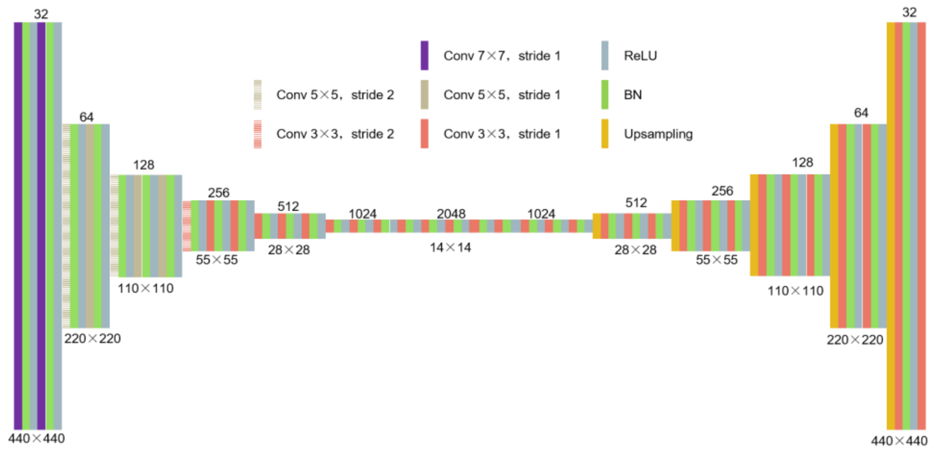

Fig. 1. The structure of VGG used in this work, 36 convolutional layers followed by batch normalization layers and rectified linear unit (ReLU) layers

from the sinogram.

As shown in figure 3, the SSIMs of test cases were close to 1. It means the reconstructed results were quite structural similar to labels. In addition, the PSNRs was about 40.

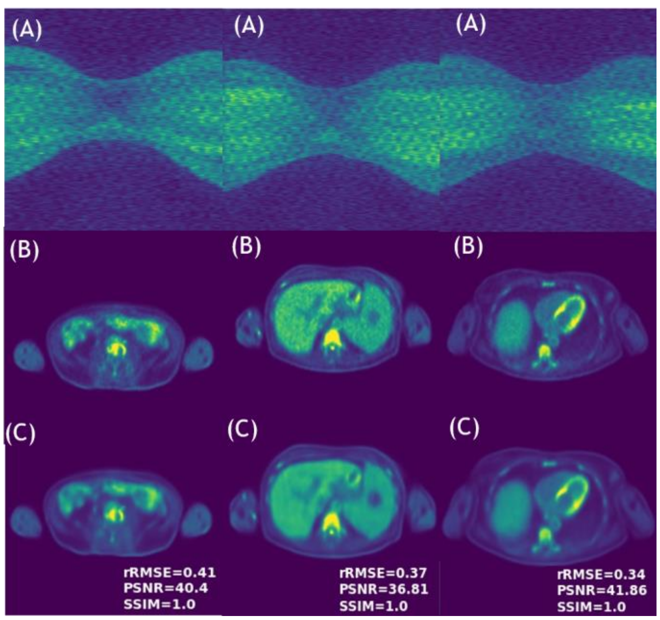

Fig. 2. Part of the test results. (A) Input sinogram data. (B) Labels(the ground truth). (C) Output results

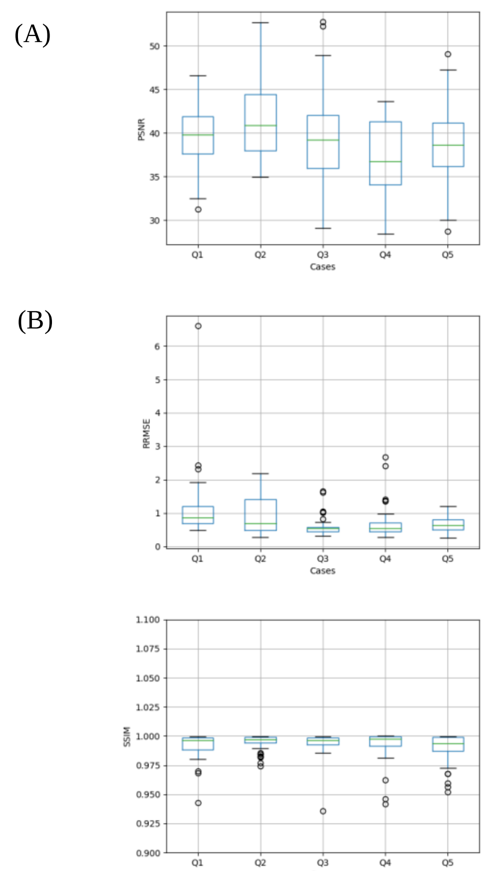

Fig. 3. Static results of 5 patients. (A) RSNR. (B) rRMSE. (C) SSIM

IV. Conclusion

The deep learning method was applied in total-body PET image reconstruction directly from sinogram data with good performance. The training database only includes 60 patients' data and more Quadra data cases will be involved in this network training. Current work is based on 2D sinogram data, and 3D reconstruction with deep learning will be further challenges, which requires more complex network structures, increased computing power, and larger memory space.

References

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