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A convolutional neural network for Y90 SPECT/CT scatter estimation

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Abstract: Monte Carlo-based scatter modeling in SPECT has demonstrated the ability on improving image quality and quantitative accuracy but high computational cost. In this study, we describe a deep learning method-based on a convolutional neural network (CNN) to increase the image quality, decrease the computation time for SPECT/CT reconstruction. Monte Carlo (MC) simulation and true scatter data are used for training and validation phase and the CNN network is trained to match the MC scatter estimation. In the testing step with a liver subject, visual image quality by CNN was better than MC scatter estimation method. Besides, the CNN scatter estimate was generated over a much shorter period of time than MC model (about 15 seconds for CNN vs ~2 hours for MC). The short processing time with CNN while maintaining quality has high clinical significance for quantitative SPECT imaging.

1. INTRODUCTION

In SPECT technique, scatter correction involves estimating the contribution of scattered gamma quanta to the photo-peak region. The scattered photons, which come from outside the detector, cause the blurring and haziness of the image, reduce the quantitative accuracy[1].

Many methods have been introduced for the correction of the scatter. Most of those methods include estimation and subtraction of the scattered contribution by using dual and triple energy window[1]. An accurate method for scatter estimation is based on Monte Carlo simulation[2,3] . However, this method is very computationally expensive. Recently, the advance of machine learning method brings the opportunity to improve the computation cost and the accuracy of MC and energy-window-based methods[4].

The work of Haowei[5] presented a method to correct the scatter using a deep convolution network. Based on this study, we have developed a new deep learning model for scatter estimation with different dataset and improving approaches. The testing results for new clinical subjects have also been presented to describe the change in contrast of SPECT images.

2. METHODS

The SPECT's projections and the projected CT-based attenuation image becomes the inputs for our CNN model, as shown in Fig 1. The estimation of scattering for each projection would be obtained. The CNN is trained to minimize the mean square error (MSE) between the output and "ground truth" data in

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the training process. In our work, the ground truth data is the true scatter simulated by MC[6,7]. Ordered Subset Expectation Maximization (OSEM) is used for SPECT/CT reconstruction[2].

2.1. Dataset

The ground truth data for the supervised CNN model was obtained from Dewaraja et al study[2,8] by MC method. The training data included: two (2 x 128 projections) SPECT phantoms, four (4 x 128 projections) Y-90 SPECT/CT subjects[2,8] and 2 (2 x 128 projections) SPECT/CT subjects for validation data with the size of 128 x 80 for each projection.

2.2. CNN architecture and training method

Figure 1 illustrates our 2D CNN architecture with 19 deep layers. We use a concatenation of SPECT's projections and CT attenuation maps as input images. According to our experiment, each branch includes 4 convolution layers with the size of 3 x 3 and the number of filters is defined as 32, 64, 128, 256 for encoder part and decrease in order of 256, 128, 64, 32 for decoder part. Following each convolution layer is batch normalization layer to normalize the output of previous layer. Our model is trained with Adam optimization, the learning rate is 0.0001, and the mean square error (MSE) is used as loss function. The CNN is trained with 500 epochs with the batch size of 50 samples with Keras. The hyperparameters are tuned and selected to avoid overfitting, work well on existing dataset and to match the power of the computer in use.

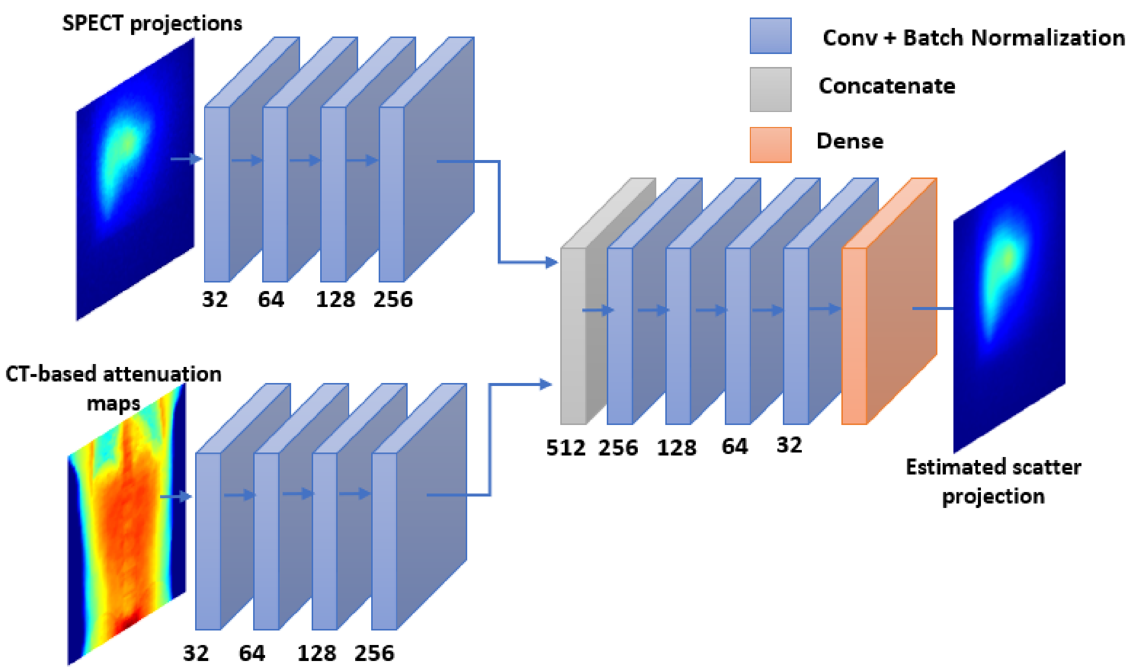

Fig. 1. The proposed CNN architecture

3. RESULTS

3.1. Training process

Figure 2 shows the dependence of MSE value on epochs for training and validation datasets. The training and validation loss decreased continuously from Figure 2. This proves that the model is not overfitting during training process. It takes 16 minutes to train on Intel (R) Core (TM) i9-10900 CPU @

2.8GHz (20 CPUs) and GPU NVIDIA GeForce RTX 1080 Ti machine.

3.2. Testing results

Reconstructed images in Figure 3 for liver subject show similar image quality with CNN and MC scatter estimates. Figure 3 shows that results from the proposed method were sharper and clearer than the MC-based results. The contrast between the liver region and the surrounding background is clearly improved in comparison with the MC method. Figure 3 also shows the sample profiles in projection domain for MC scatter estimation and CNN scatter estimation. These two curves are almost the same.

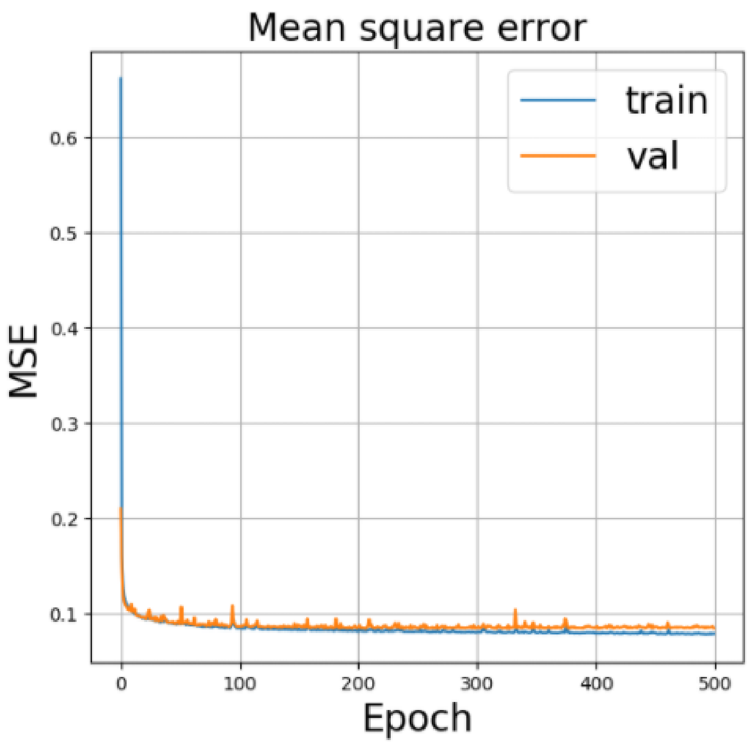

Fig. 2. MSE vs. epochs for training and validation datasets

4. DISCUSSION

In this study, image quality with the CNN scatter estimation method showed the same result as of Monte Carlo-based approach. In addition, the CNN scatter estimate is generated over a much shorter period of time than MC model. This is of particular clinical significance when time is of the essence. Our study used limited data, so we will collect more data from some hospitals in Vietnam and perform quantitative assessments in the future studies.

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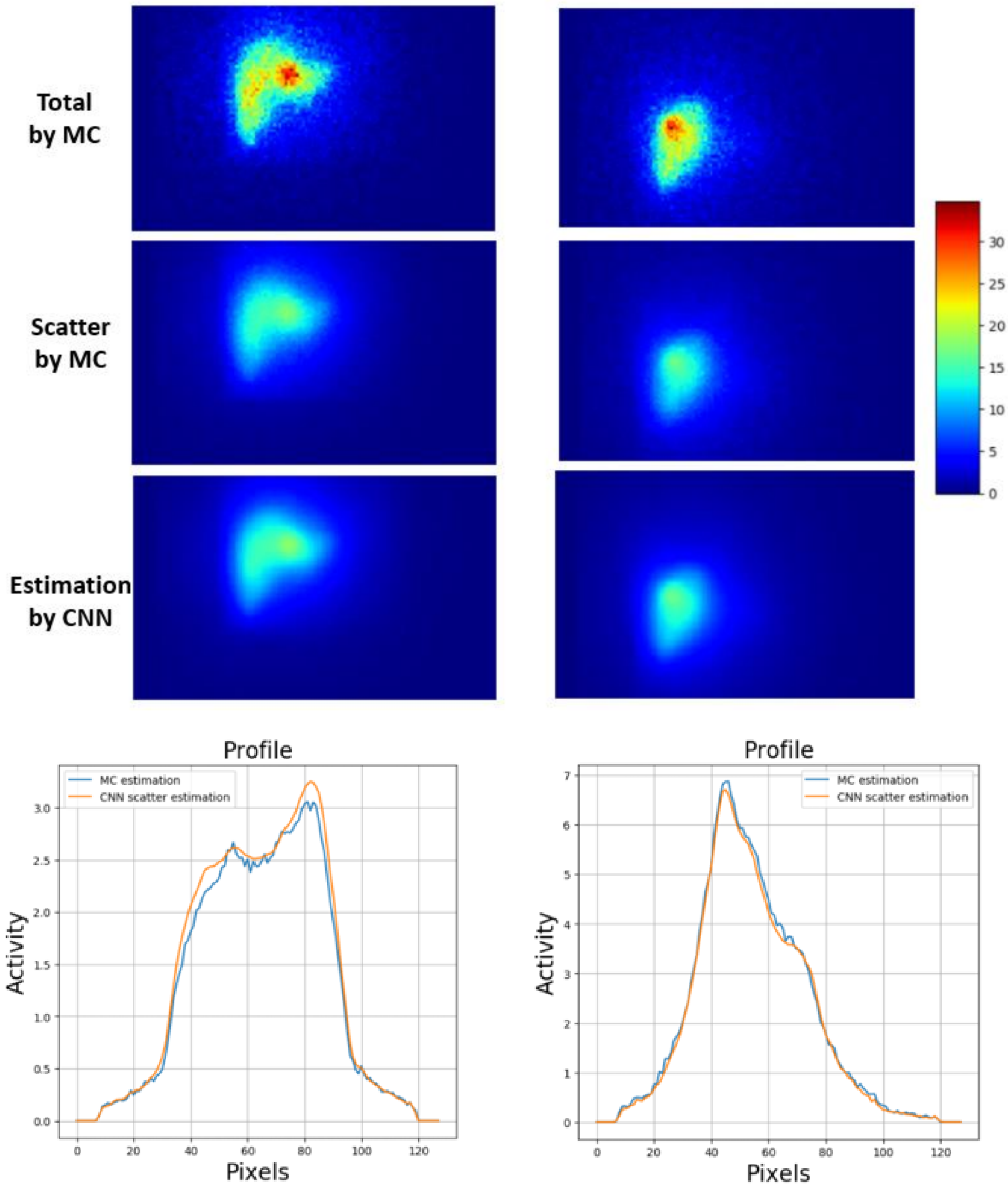

Fig. 3. Reconstructed slices with MC, CNN and total by MC scatter estimates and sample profiles in projection domain for 2 above slices.

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