A solution for scatter estimation problem in simultaneous reconstruction, and its impact on deep learning based attenuation correction

Donghwi Hwang[1], Kyeong Yun Kim[2], Hongyoon Choi[1], and Jae Sung Lee[1,2,*]

[1]Dept. of Nuclear Medicine, Seoul Nat'l Univ., Seoul, Korea

[2]Brightnoix Imaging Inc., Seoul, Korea

Objectives: In our previous works, a deep learning-based μ-map generation approach using maximum likelihood reconstruction of activity and attenuation (MLAA) was proposed, showing only attenuation correction (AC) error of about 2% compared to CT AC. However, there is a chicken-egg dilemma of scatter estimation. Scatter events are required for conducting MLAA, but estimating scatter events requires μ-maps. To address this issue, the scatter events were derived from CT μ-maps (μ-CT) and assumed to be known in the previous works, which was a crucial limitation. The aim of this study was to solve the scatter estimation problem in MLAA and validate this approach.

Methods: Hundred oncologic patients underwent whole-body F-18-FDG PET scans using a Siemens Biograph mCT 40 scanner. The cases were divided into training (N=60), validating (N=20), and testing (N=20) sets. All data sets were reconstructed using non-attenuation corrected (NAC) OSEM with TOF information. A network (CNN1) based on 3D U-net architecture was employed to generate μ-maps (μ-CNN1) from NAC activity images (λ-NAC). From this μ-map, scatter events were estimated using single scatter simulation (SSS) with the assumption that scatter estimation from μ-CNN1 may not lead to significant errors as the scatter distribution is blurry spread and gradually varying. With this estimated scatter, activity and attenuation maps were obtained using MLAA (λ-, μ-MLAA) with TOF information. Then, a more improved attenuation map was generated by networks using either λ-NAC and/or λ-, μ-MLAA (CNN2 and CNN3, respectively). To validate scatter estimation accuracy, errors in scatter distributions and attenuation coefficient factor (ACF) between μ-CNN1 and μ-CT were measured. To evaluate the accuracy of network-generated μ-maps (μ-CNNs), normalized root-mean-square error (NRMSE) of μ-maps relative to μ-CT were measured. Also, to assess the reliability of AC, we compared the activity images reconstructed using OSEM with TOF information for each μ-CNN using SUV of lung lesions. In addition, we calculated the voxel-wise correlation with CT, not only for μ-maps but also for activity images reconstructed using OSEM with the corresponding μ-maps.

Results: The mean squared error of ACF was over 10% (10.8% ± 2.5%), but the mean squared error of scatter distribution was only 3% (3.2% ± 0.1%), compared to CT-derived ones. Some lung lesions in μ-CNN1 were excessively large, which resulted in SUV

overestimation. On the other hand, CNN2 that employed scatter estimation from CNN1 generated μ-maps more similar to μ-CT. With aid of NAC input, CNN3 generated μ-maps with better bone identification and lower NRMSE than other μ-CNNs (CNN1: 0.050 ± 0.014, CNN2: 0.032 ± 0.010, CNN3: 0.031 ± 0.007). In the activity images reconstructed using these μ-CNNs, CNN3 achieved the highest voxel-wise correlation with μ-CT (CNN1: y=0.91x+0.08, R^2=0.77; CNN2: y=0.92x+0.07, R^2=0.90; CNN3: y=0.96x+0.04, R^2=0.90). In SUV quantification of lung lesions, the slope of the linear regression line of CNN1 was almost 1, but the y-intercept was largest with a positive bias. CNN3 showed the best accuracy.

Conclusion: The errors in μ-CNN1 did not propagate to the scatter estimation. Therefore, despite the insufficient accuracy of μ-CNN1, the scatter estimation from μ-CNN1 could be employed for the scatter correction in MLAA, providing a solution to the scatter problem. Moreover, the NAC approach allows further improvement of μ-CNN by incorporating NAC as an input to the network.