Deep Learning-Enabled Scan Parameter Normalization of Imaging Biomarkers in Low-Dose Lung CT

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***Abstract*—CT scan parameters are known to strongly affect imaging biomarker quantification and increase variability of measurements. We present a deep learning-enabled recon kernel normalization technique and its effect in emphysema quantification in low-dose lung CT.**

Keywords: Emphysema index, Reconstruction kernel, Deep learning, Convolutional neural network.

I. Introduction

Differing reconstruction kernels are known to strongly affect the variability of CT imaging biomarkers and thus remain as a barrier in translating the computer aided quantification techniques into clinical practice [1]. Previous studies attempted various approaches including empirical correction of measured data, application of simple mathematical model of CT system function in data extraction process, use of filter bank set for data normalization. Studies showed, however, conventional techniques allowed only a limited success in normalizing imaging markers in CT imaging.

In this study, we present a deep learning application to CT kernel conversion which converts a CT image of sharp kernel to that of standard kernel and evaluates its impact on variability reduction of a pulmonary imaging biomarker, the emphysema index (EI)..

II. Maeterials and Methods

A total of 3450 low-dose chest CT images obtained with 120kVp, 40mAs, 1mm thickness, of two reconstruction kernels (B30f, B50f) were selected from the low dose lung cancer screening database of our institution. The B50f is a 'sharp' kernel and frequently used to reconstruct "for read" images for making visual diagnosis, while the B30f is a 'soft' kernel and used to reconstruct "for measure" images for quantitative analysis of emphysema index (EI).

Our study attempted to translate a CT scan obtained with B50f into that with B30f by using a deep learning –based kernel conversion technique. A U-Net type deep learning model was created with PyTorch deep learning toolkit [2]. The model consisted of symmetric layers to capture the context and fine structure characteristics of CT images from the standard and sharp reconstruction kernels. Pairs of the full-resolution CT data set were fed to input and output nodes to train the convolutional network to learn the appropriate filter kernels for converting the CT images of sharp kernel to standard kernel with a criterion of measuring the mean squared error between the input and target images. The EI (RA950) was measured with a software package (ImagePrism Pulmo, Seoul, South Korea) and compared for the data sets of B50f, B30f, and the converted B30f. The effect of kernel conversion was evaluated with the mean and standard deviation of pair-wise differences in EI.

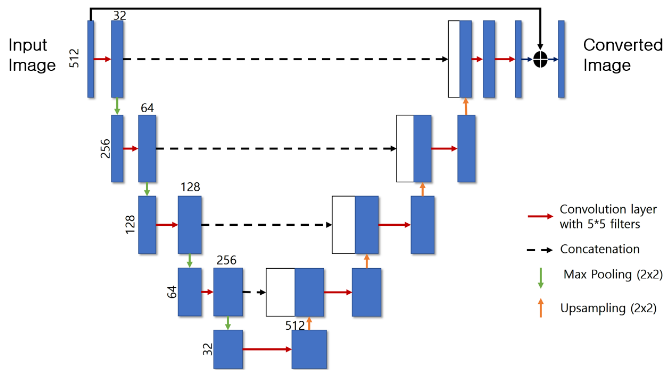
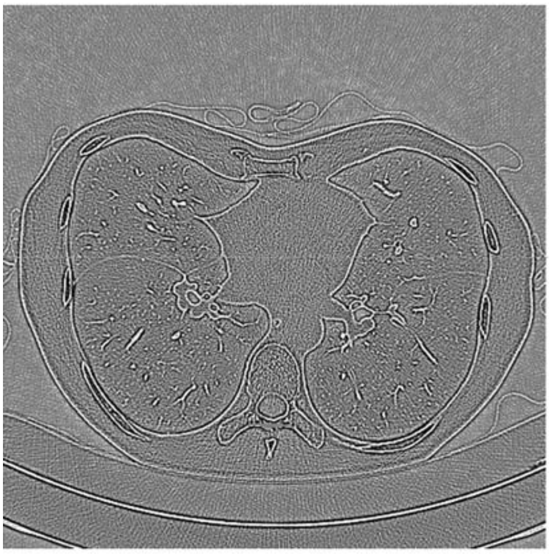


Fig. 1. Structure of the U-net type deep learning model used in this study.

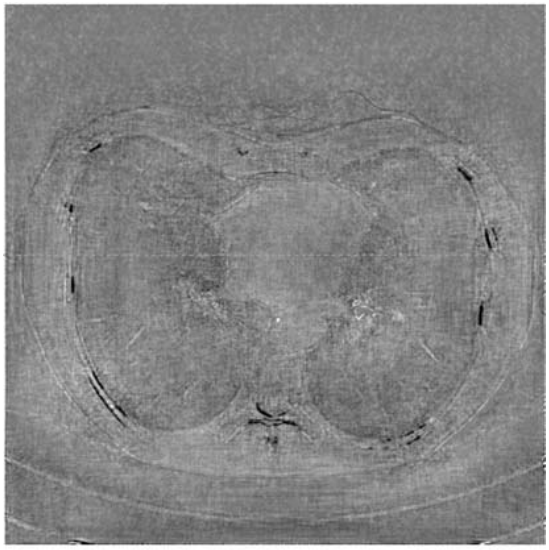
III. Results

Fig. 2 compares example difference images between B50f and B30f before and after applying the deep learning mode. The difference image before applying the deep learning technique shows significant amount of residuals on structure edges and sharp parenchymal tissue, whereas the residuals were substantially reduced in the difference image after applying the deep learning technique.

The population mean of EI was 24.37±8.64% for B50f data set, 8.77±9.41% for the B30f data set, and 10.49±11.22% for the converted B30f data set. The mean pair-wise difference in EI between B50f and B30f was reduced from 15.62% to 1.72% after deep learning-based kernel conversion. Fig. 3 compare the Bland-Altman plots of EIs for the CT scans with B50f and B30f before kernel conversion with that after kernel conversion. It is evident that the strong bias of EI with B50f was substantially reduced after kernel conversion.



Difference Image : B50f$_{org}$ - B30f

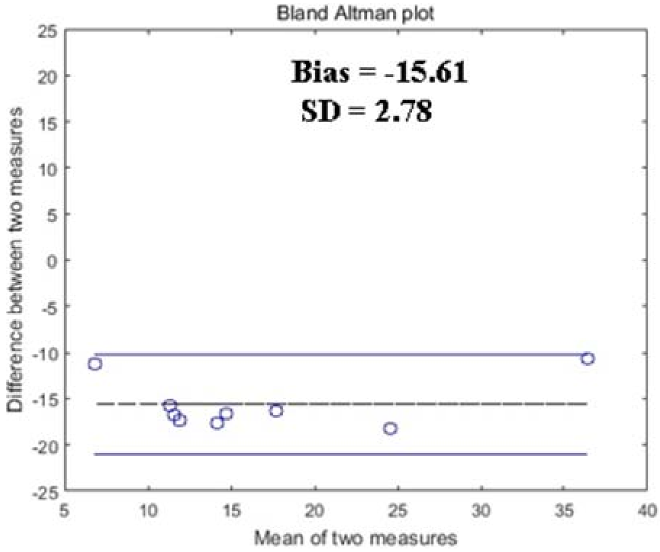


Difference Image : B50f$_{cnv}$ - B30f

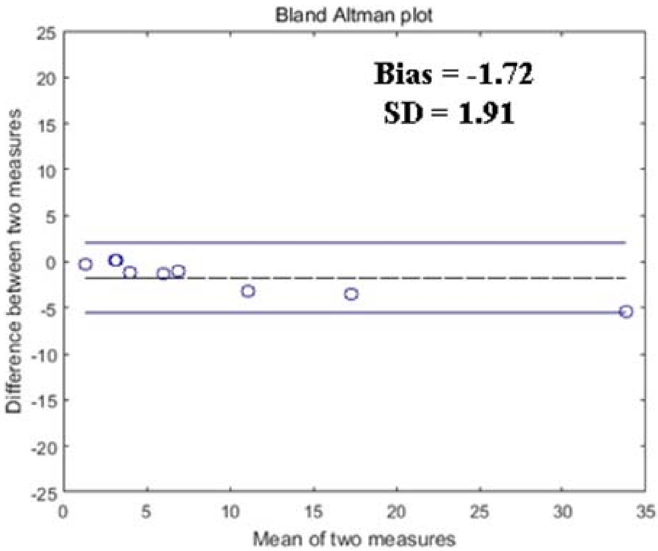
Figure 2. Example difference images between B50f and B30f before and after applying deep learning-based kernel conversion technique.

IV. Conclusion

Our study demonstrates the potential of the deep learning technique for CT kernel conversion and reducing the kernel-induced variability of imaging biomarker, especially for EI quantification. The deep learning model is promising for improving the reliability of imaging biomarker, especially in evaluating the longitudinal changes of EI even when the patient CT scans were performed with different kernels.



(a)



(b)

Figure 3. Comparison of Bland-Altman plots for (a) EI with B30f and B50f before applying kernel conversion, and (b) After applying kernel conversion. The kernel-induced variability was reduced close to zero.

References

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