Deep Learning-Based Scatter Correction for Dual Source CT

Editors: Under Review for MIDL 2020

Abstract
Dual source CT (DSCT) use two source-detector pairs offset by about 90 degree. An issue in DSCT is cross-scattered radiation from X-ray tube A detected in the detector of system B and vice versa. This effect can lead to artifacts and reduction of the contrast-to-noise ratio of the images. To correct for these scatter artifacts in DSCT we present a deep learning-based scatter estimation method. A deep convolutional neural network is trained with scatter intensities obtained from our Monte Carlo simulation. The proposed method is able to correct for most of the scatter artifacts and outperforms measurement-based scatter correction in term of image quality.

Keywords: dual source computed tomography, DSCT, x-ray scatter, cross-scatter, scatter correction, image quality, artifacts, imaging performance

1. Introduction
Dual source CT (DSCT) systems use two measurement threads, A and B, offset by an angle of 90 or 95 degree depending on the system. The doubled angular coverage leads to doubled temporal resolution which is especially profitable in time critical applications like cardiac CT (Kachelrieß et al., 2006; Flohr et al., 2008). A crucial challenge in DSCT is cross-scattered radiation in addition to the well known forward scattered radiation (Figure 1). This effect can lead to artifacts and reduction of the contrast-to-noise ratio of the images. Scatter correction algorithms are mandatory to mitigate the negative effect of the scattered radiation (Petersilka et al., 2010). For the correction of forward scatter the deep scatter estimation method has been presented recently which uses a deep convolutional neural network (CNN) to estimate the forward scatter intensity using the acquired projection data as input (Maier et al., 2018, 2019). We present a new method for correcting cross-scatter artifacts in a DSCT scan.

2. Materials and Methods
The scatter profiles for the training of our neural network are obtained by our in-house Monte-Carlo simulation The simulated geometry is adapted to the scanner Somatom Force Siemens Healthineers. In total 19 patients at 14 z-positions are simulated every 10 degree. The training data set consists of 15 patients, while 4 patients are used for validation. Cross-scatter intensities are estimated using a convolutional autoencoder architecture. The network consists of 6 convolutional encoding blocks and 6 convolutional decoding blocks. Downsampling is ensured by maxpooling layers whereas upsampling steps use transposed convolutions with appropriate stride increments. As cross-scattered radiation is mostly
Deep Cross-Scatter Correction

3. Results and Conclusion

The proposed method clearly improves the image quality of the reconstructed images (Figure 2). Almost all dark streaks induced by the cross-scatter radiation are removed. Our correction technique outperforms the measurement-based scatter correction in terms of visual perception and MAE on simulated data. In a next step, a thorough clinical evaluation will be performed by applying our cross-scatter estimation on CT measurements and re-
constructing the images. A combination of forward and cross scatter correction will also be evaluated.

Figure 2: Comparison of different cross-scatter correction methods for two different patients. The reconstructed images show a) ground truth (GT), b) uncorrected, c) measurement-based correction d) proposed method ($C = 40$ HU, $W = 300$ HU). Below the reconstructed images the difference to the GT is shown ($C = 0$ HU, $W = 300$ HU).

References


Appendix A. Loss-function

Situations with large attenuation can lead to strong cross-scatter artifacts if not corrected. To consider this in the cross-scatter correction the SPMAPE (scatter-to-primary-weighted mean absolute percentage error) is used as loss function. We define $I_{\text{scatter,DSE}}$ the scatter intensity estimated by the neural network and $I_{\text{scatter,MC}}$ obtained by Monte-Carlo simulation. With $I_{\text{prim}}$ as primary signal and with $N$ the number of detector pixels the our loss function is

$$\text{SPMAPE} = \frac{1}{N} \sum \left| \frac{I_{\text{scatter,MC}} - I_{\text{scatter,DSE}}}{I_{\text{scatter,MC}}} \times \frac{I_{\text{scatter,MC}}}{I_{\text{prim}}} \right|$$

$$= \frac{1}{N} \sum \left| \frac{I_{\text{scatter,MC}} - I_{\text{scatter,DSE}}}{I_{\text{prim}}} \right|. $$