**Unsupervised Deep Scatter Estimation (uDSE) and Correction for CT and CBCT**

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**Purpose**

Recently, neural networks have proven great potential for scatter estimation and scatter correction in CT and CBCT. However, existing correction approaches rely on supervised training strategies, and thus, on the quality and the availability of labeled data. Since several applications lack such data, this study investigates the feasibility of implementing a neural network-based scatter estimation and correction in an unsupervised manner, i.e. without having prior knowledge of the scanner's x-ray and scatter properties

**Materials and Methods**

Scatter correction approaches are typically based on complex theoretical models, or more recently, on neural networks that make use of such models during training, e.g. by being trained to reproduce the output of Monte Carlo simulations. However, due to the strong dependence on precise prior knowledge (x-ray spectrum, detector response, etc.), it is often challenging to get these models in agreement with measurements. Therefore, we propose the unsupervised deep scatter estimation (uDSE), which does not rely on an explicitly defined theoretical model but is based on a generative adversarial network (GAN). The basic workflow of the proposed uDSE approach is shown in figure 1. Here, the uDSE generator is composed of a U-net-like scatter estimation network that predicts the scatter distribution for an input projection, a correction layer that uses this prediction to perform a scatter correction (e.g. by subtraction), and an FBP layer that reconstructs the corrected projections. While the weights of the FBP and the scatter correction layer are fixed, the ones of the scatter estimation network are optimized to fool a discriminator network that is trained simultaneously to recognize scatter artifact-free CT reconstructions.

In this preliminary study, we demonstrate the feasibility of the proposed approach using 2D CT simulations. To do so, a scatter-corrupted data set consisting of 10,000 samples was generated by forward projecting clinical CT images and by adding scatter in intensity domain according to the model of Ohnesorge et al. [Eur. Radiol. 9, 563-569 (1999)]. While this data set was used as input to the generator network, another set of 10,000 clinical CT images without artifacts was used to train the discriminator. The training was performed on an NVIDIA GeForce RTX 2080 Ti for 200 epochs using an Adam optimizer and a learning rate of $10^{-5}$. Finally the proposed approach was evaluated on an independent testing data set and compared against DSE [Med. Phys. 46(1):238-249 (2019)], our supervised deep scatter estimation approach.

**Results**

Exemplary results of uDSE on the test set are shown in figure 2 for different anatomical regions. In any case, uDSE efficiently removes the present scatter artifacts and yields images that are almost equal to the ground truth. Evaluating the accuracy of the scatter corrected CT reconstructions for all testing data with respect to the ground truth yields a mean absolute percentage error (MAPE) of about 7 %. Compared to the supervised reference which achieves a MAPE of 4 %, the quality of the scatter prediction is only slightly degraded.

**Conclusion**

Our results demonstrate the feasibility of training a neural network to estimate scatter distributions in an unsupervised manner. While this study provides a proof of principle using 2D simulations, there are no restrictions to extend the proposed approach to 3D as well as to real measurements. Thus, uDSE has the potential to extend the concept of neural network-based scatter estimation and correction to scenarios where labels are not available or cannot be generated with sufficient accuracy.

**Limitations**

This study is limited to 2D simulations.

**Ethics committee approval**

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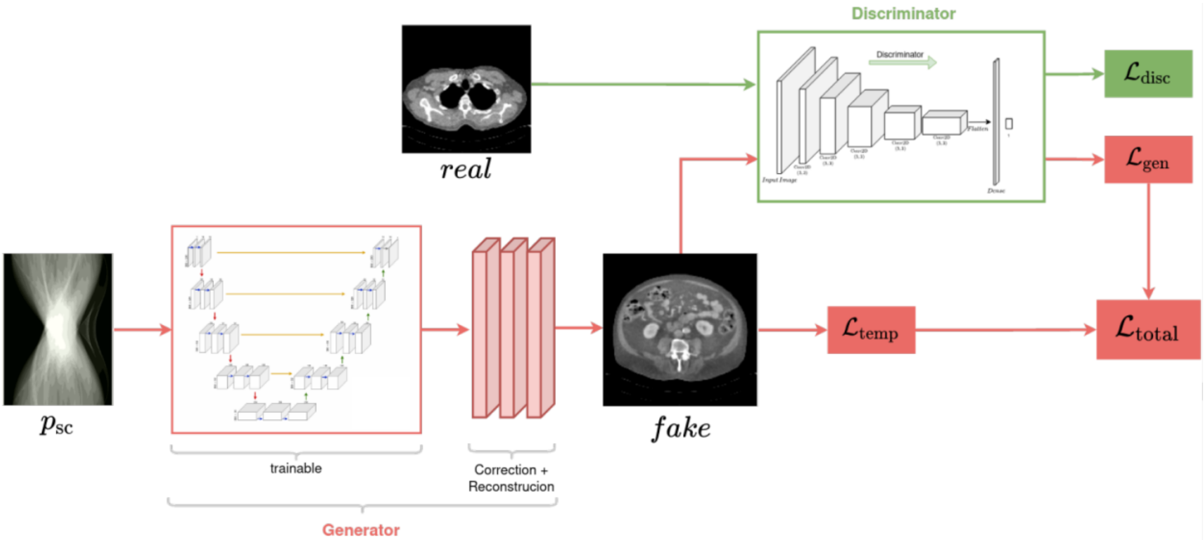


**Figure 1:** Schematic of the proposed GAN approach. A U-net-like scatter estimation network is used to predict the scatter content of the input sinogram ($p_{\mathrm{sc}}$). Subsequently, the scatter prediction is subtracted in intensity domain and the so corrected sinogram is reconstructed by an internal FBP layer. Here, the weights of the generator network are optimized to fool a discriminator network which is trained simultaneously to recognize scatter artifact-free CT reconstructions.

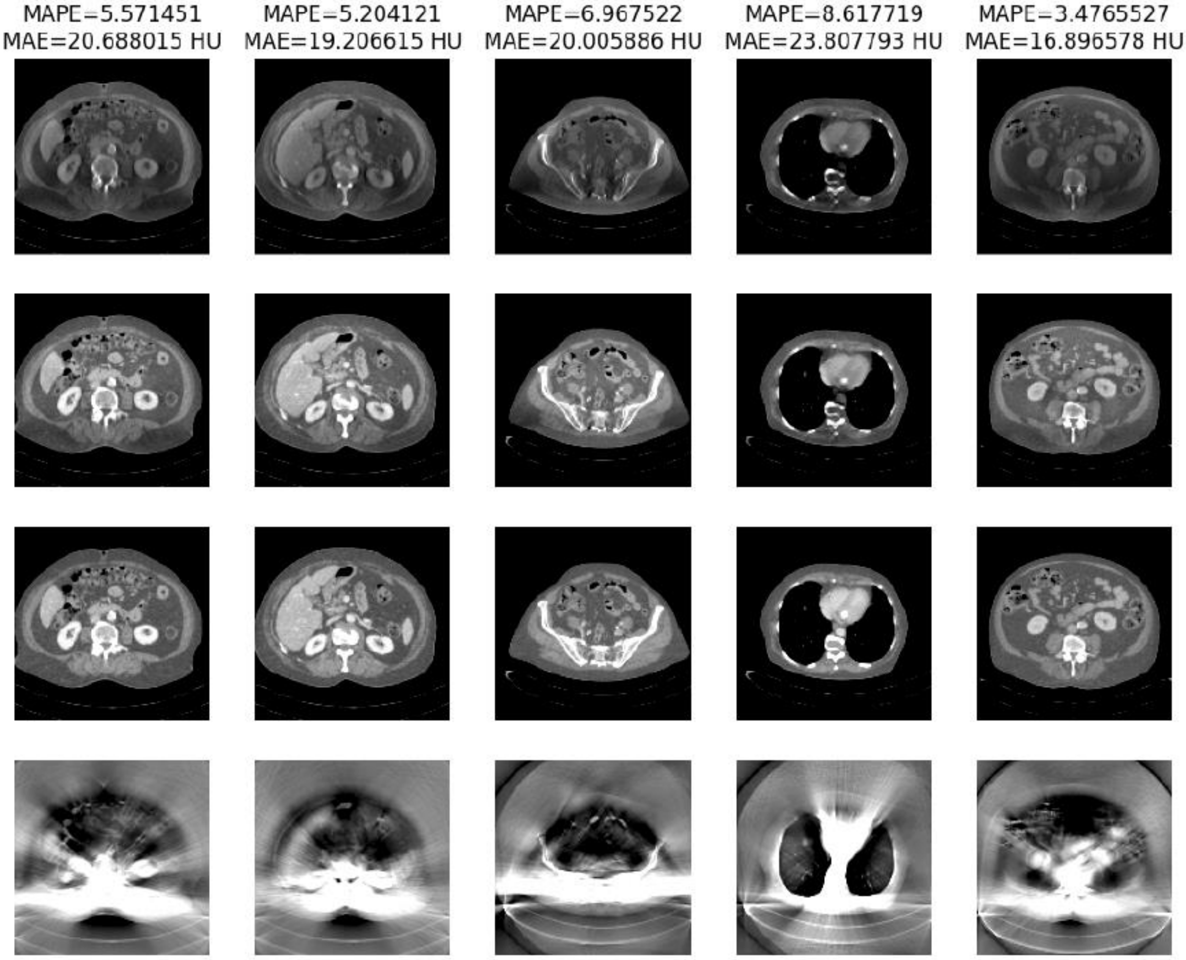


**Figure 2:** Exemplary uDSE correction results for different anatomical regions. First row: uncorrected input; second row: scatter correction; third row: ground truth; fourth row: difference image. All images are windowed with *C* = 0 HU, *W* = 700 HU.