Deep Grid Inpainting for Photon-Counting CT Detectors

Jan Magonov [1,2,3], Joscha Maier[1], Eric Fournié[2], Johan Sunnegårdh[2], Karl Stierstorfer[2], and Marc Kachelrieß[1,3]

[1]German Cancer Research Center (DKFZ) Heidelberg, Division of X-Ray Imaging and CT, Germany
[2]Siemens Healthineers AG, Computed Tomography Division, Germany
[3]Heidelberg University, Medical Faculty, Germany

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Introduction

Photon-counting computed tomography (PCCT) uses very small detector pixels that are typically smaller than in conventional energy-integrating systems (see Figure 1). The anti-scatter grid (ASG) used for minimizing scattered radiation, blocks the primary radiation behind the ASG lamellae, which can lead to dead rows and columns on the detector. A sophisticated inpainting algorithm is required to avoid possible artifacts in reconstructed images. We propose the grid inpainting with deep learning (GRIDL), a neural network-based algorithm for inpainting defined patterns of gaps in column and row direction.

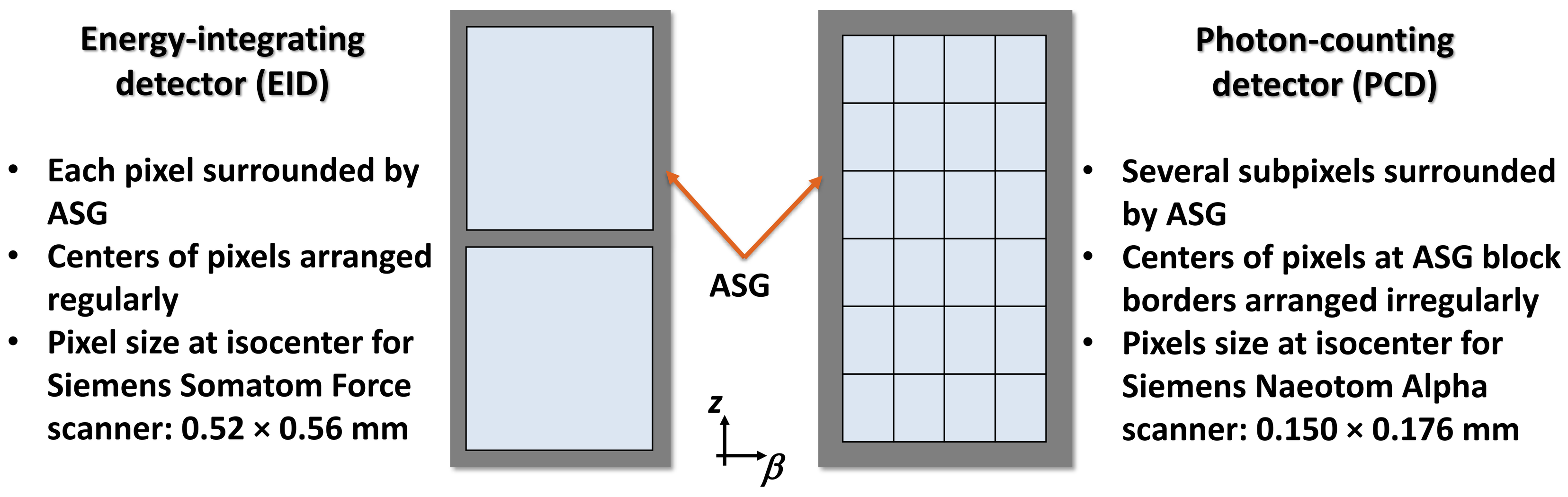

Figure 1: Comparison between energy-integrating and photon-counting detector layout.

Material and Methods

A convolutional neural network [1, 2] is trained using a binary mask to inpaint gaps in detector images. This mask preserves existing pixel values, enabling the network to learn the mapping between input images and the necessary pixels to fill gaps. Network architecture shown in Figure 2. After network inference, the output is merged with the original image to replace missing pixels. Initial experiments involved corrupting gapless EID data with regularly patterned artificial gaps, mimicking the ASG arrangement in the Siemens Naeotom Alpha PCCT scanner.

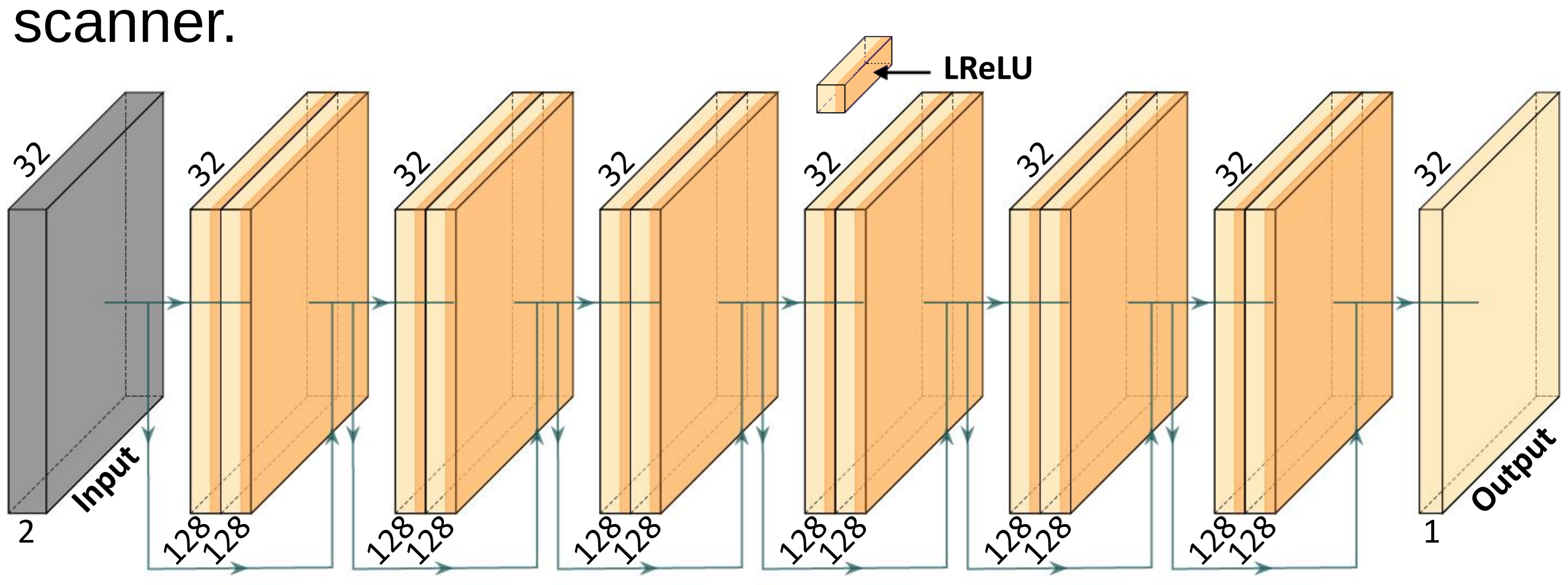

Figure 2: GRIDL network architecture consisting of 12 2D convolutional layers (filters = 128, kernel size 3x3, stride 1x1, zero padding) with individual activation by leaky rectified linear units (LReLU). Skip connections are employed between the output of every two convolutional layers with the output of the preceding block. Network training involves random 32x32 pixel sized patches. A binary mask indicating the gaps is provided as second input channel.

Network training was performed using an experimental dataset of simulated projection data involving a phantom with randomly arranged spherical shells (diameter: 1 – 20 cm, density: 0.5 – 3.0 g/cm^3). In total 100 spiral CT scans with randomly arranged phantoms were simulated noise-free in EID geometry to obtain ground truth detector images without gaps. Figure 3 illustrates the generation of training data patches. The training process involved 500,000 patch pairs for training and 125,000 pairs for testing while minimizing a combined loss function incorporating the mean absolute error and multi-scale structural similarity index.

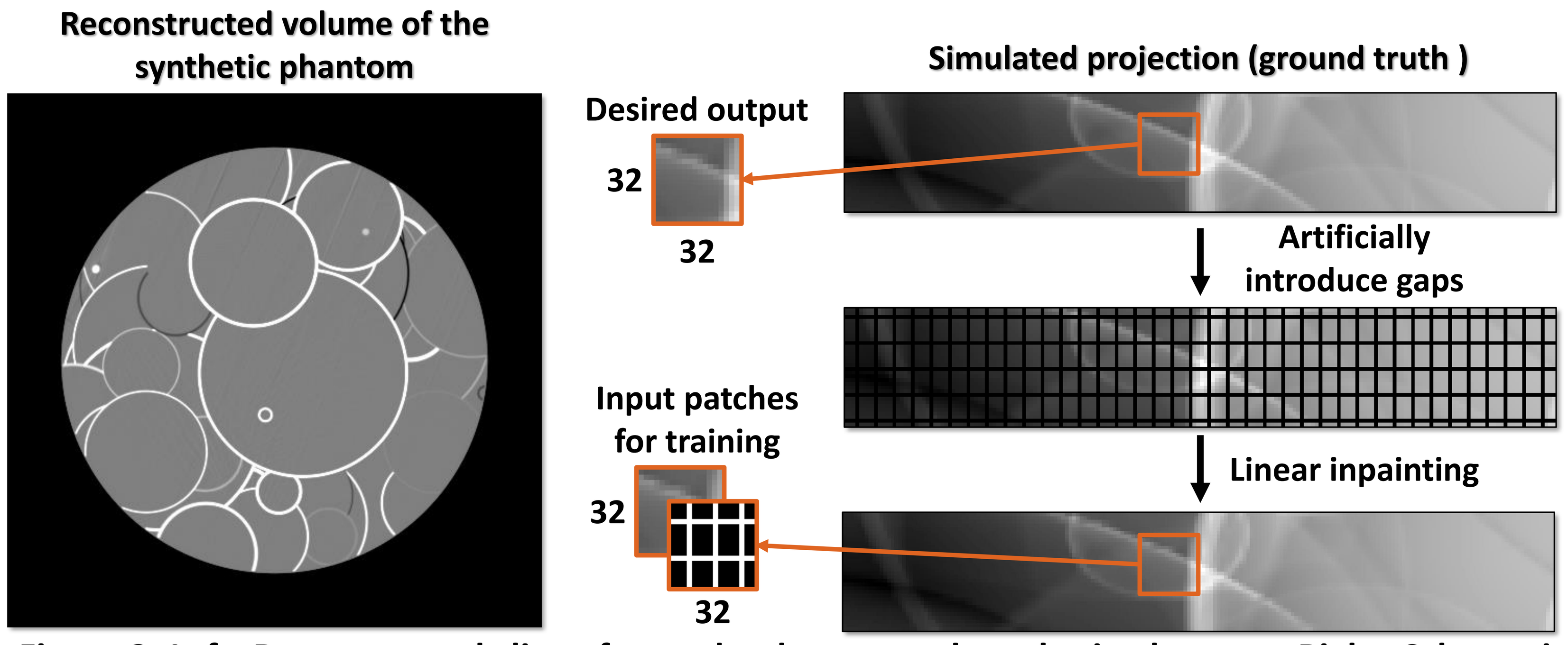

Figure 3: Left: Reconstructed slice of a randomly arranged synthetic phantom. Right: Schematic representation of training patch generation. Simulated projection data are corrupted by a pattern of artificial gaps. Next, a linear interpolation is used as initialization for GRIDL. Random patches with a size of 32×32 pixels from the corrupted projections together with corresponding mask patches in the second channel are used as network input. Corresponding patches from the ground truth projections are used as label.

Results

The performance of GRIDL was evaluated using a head phantom scan. Artificial gaps were introduced, as described before. After inpainting the projection data with GRIDL, the results were compared to corresponding reconstructions of projection data which were inpainted using biharmonic diffusion [3, 4] and with reconstructions of the gapless detector images as shown in Figure 4.

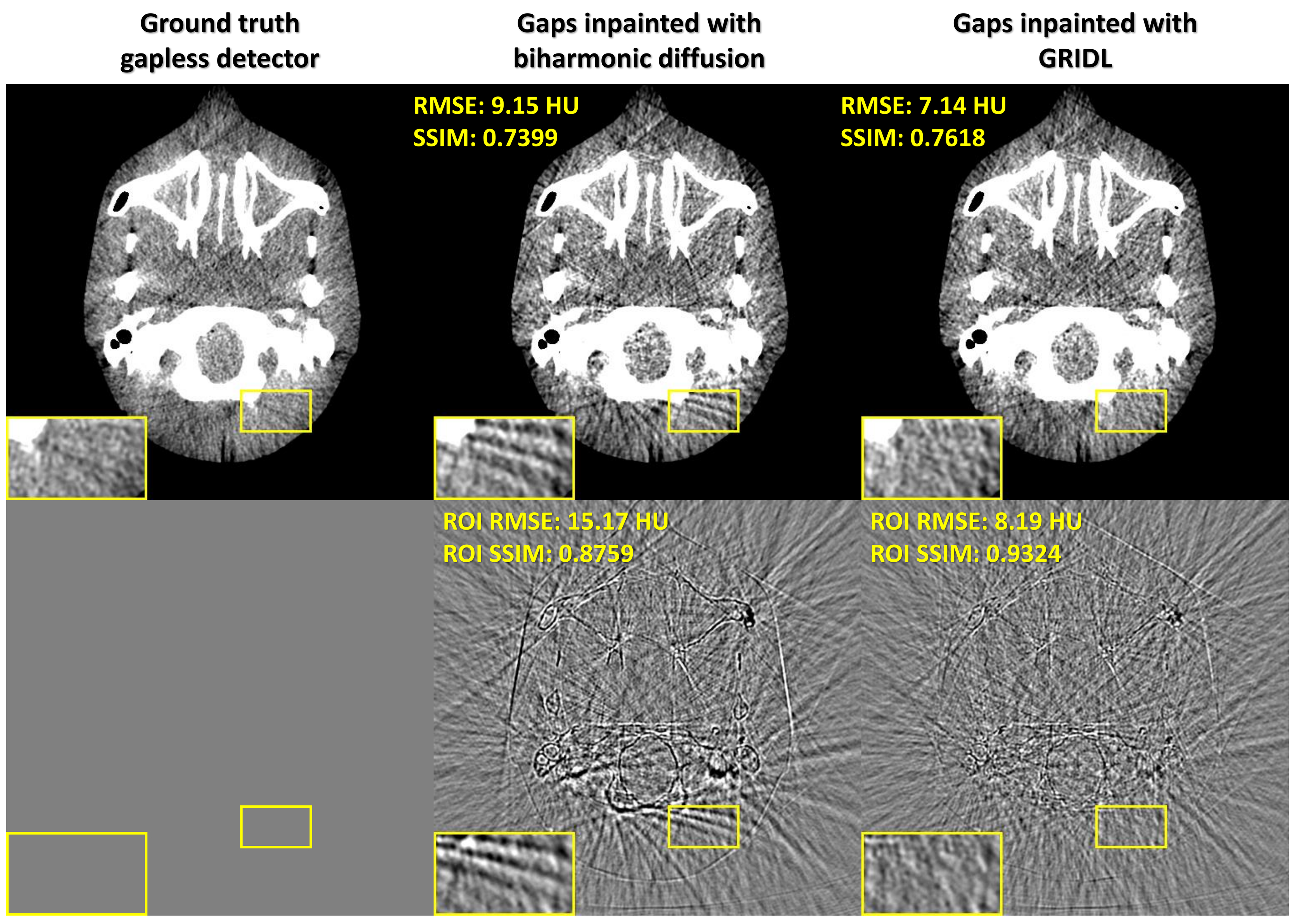

Figure 4: Comparison of a reconstructed slice between the gapless ground truth data and the inpainted data with a diffusion-based inpainting and GRIDL. CT images: *C* = 20 HU, *W* = 80 HU. Difference images to ground truth: *C* = 0 HU, *W* = 70 HU. Reconstructed slice width: 0.75 mm.

The reconstruction involving a diffusion-based inpainting suffers from several artifacts in image domain. In comparison GRIDL improves the image quality and leads to more comparable results to the ground truth. A quantitative evaluation supports this finding, given that the RMSE calculated for the entire head and the selected ROI is reduced and the SSIM is increased in both cases with GRIDL.

Conclusions

GRIDL successfully inpaints the ASG-like gap pattern and leads to superior image quality compared to a diffusion-based inpainting approach while reducing aliasing artifacts.

[1] Magonov, Erath, Maier, Fournié, Stierstorfer, and Kachelrieß. *Deep Learning-Based Detector Row Upsampling for Clinical Spiral CT*. SPIE. 2022.
[2] Magonov, Maier, Erath, Sunnegårdh, Fournié, Stierstorfer, and Kachelrieß. *Reducing Windmill Artifacts in Clinical Spiral CT using a Deep Learning-Based Projection Raw Data Upsampling: Method and Robustness Evaluation*. Med Phys. 2024;1-20.
[3] Van der Walt, Schönberger, Nunez-Iglesias, Boulogne, Warner, Yager, Gouillart, and Yu. *Scikit-Image: Image Processing in Python*. PeerJ. 2014.
[4] Damelin, and Hoang. *On Surface Completion and Image Inpainting by Biharmonic Functions: Numerical Aspects*. Int J Math Math Sci. 2018;1-8.

Correspondence: jan.magonov@dkfz.de

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This study is supported by Siemens Healthineers AG.