Mixed-Scale Dense Convolutional Neural Network based Improvement of Glass Fiber-reinforced Composite CT Images

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Summary: For the study of glass fiber-reinforced polymers (GFRP), μCT is the method of choice. Obtaining GFRP parameters from a μCT scan is difficult, due to the presence of noise and artifacts. We propose a method to improve GFRP image quality using a recently introduced deep neural network. We describe the network's setup and the data generation and show how the trained network improves the reconstruction.

1. Introduction

Glass fiber-reinforced polymers (GFRP) are versatile components whose mechanical properties are mainly determined by the spatial statistics of the fibers in the polymer. X-ray μCT is a popular imaging method to study the internal structure of those composites in a nondestructive way, with a high spatial resolution. The quality of the reconstructed μCT image, and with that the quality of the estimated fiber statistics, depend on several acquisition settings, such as the number of projections and the scanning geometry [1]. In a typical scenario, thousands of radiographs are required for a high quality reconstruction, which results in long scan times and large datasets [2]. We propose an improvement of GFRP reconstructions from a limited number of radiographs using a mixed-scale dense convolutional neural network (MSDNN)[3]. We show that using the network improves the reconstruction significantly.

2. Methods

We randomly generated fiber datasets using the Random Sequential Adsorption algorithm [5], modelling the background as solid material with value 0.23 and the fibers as cylinders with gray value 0.76. The intensities are normalized to $[0, 1]$ and are based on the gray values of a real GFRP sample [4]. For the generation of the radiographs we used a circular cone beam geometry. Furthermore, we added Poisson noise corresponding to signal-to-noise ratios (SNR) ranging from 10 to 160 to the projections, to emulate realistic acquisitions.

The images were then reconstructed from the radiographs using SIRT [6]. For each dataset, we generated 100 equidistantly spaced projections with varying starting angles. However, using a limited number of projection angles induces so called *streaking artifacts*. These artifacts extend perpendicular to the rotation axis, getting stronger away from the center. The starting angles were varied to avoid the artifacts being in the same location within every reconstructed volume. To that end we also varied the phantom's orientation and the number and direction of the fibers to include subtle misalignments in the geometry in the training data.

The MSDNN [3] was trained to learn how to remove those artifacts along with the noise. The mean squared error (MSE) between the network output and the ground truth was used as loss function. In total, we generated 128 datasets, training the network on 112 with a limited SNR in the range of 45 to 130 and verified our results on the 16 remaining ones that covered the full range of SNRs. The training was stopped as soon as either four consecutive epochs (One epoch has passed when the entire set of datasets is passed through the network once) did not improve the MSE, or if 300 epochs passed.

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3. Results

To test the trained network we applied it to 16 datasets with increasing SNR and compared their MSE to the ground truth. Figure 1a shows a reconstruction and its MSDNN improved version. The remaining artifacts are barely noticable. In Figure 1b, the MSE of our test training sets as a function of the SNR is visualized. The SNR for Poisson noise is $\sqrt{N}$, with N the number of detected photon counts in the background. It can be seen that the network improves the MSE by an order of magnitude over the SIRT reconstruction, which also uses MSE as a feedback mechanism for its iterations. The lowest and the highest three SNR values in Figure 1b are outside of the SNR range used in the training set, which shows the network generalization in removing the noise for a wide range of SNRs.

4. Conclusion

We showed that using the trained MSDNN improves the MSE of the reconstruction by around one order of magnitude and can even improve noisy data with noise levels it was not trained on. This will make it possible to more accurately quantify fiber data even with a low number of projections.

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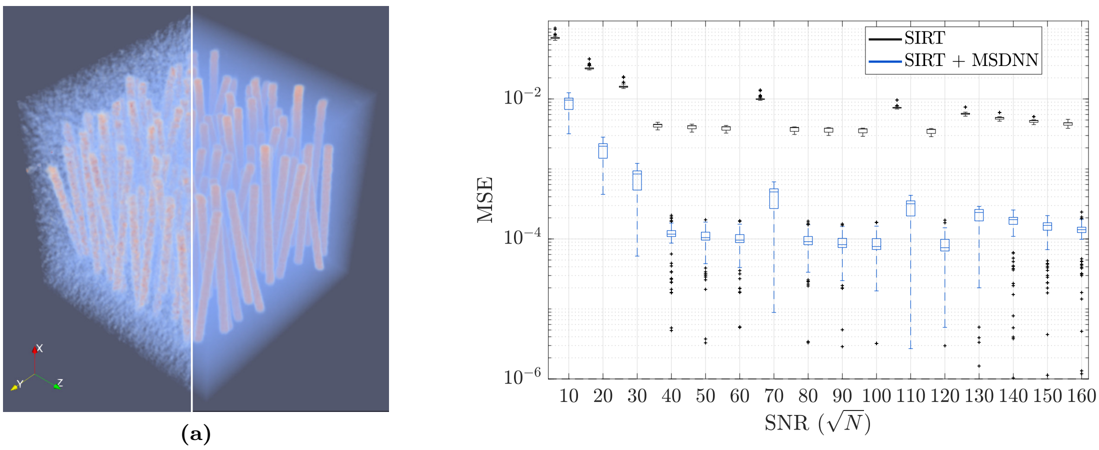

(b)

Figure 1: (a) Reconstruction of a phantom (MSE $\approx 8.7 \times 10^{-3}$) (left) and neural network improved reconstruction (MSE $\approx 4.1 \times 10^{-4}$) (right) (b) Boxplot depicting the MSE as a function of the noise level for the SIRT reconstruction and the MSDNN corrected SIRT reconstruction.