AI Analysis Basic Course
Third Installment: Improvement of Image Quality and Analysis Accuracy of X-ray CT Reconstruction Images by Deep Learning

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Abstract

In this article, we present a method for improving the image quality of X-ray CT reconstruction images using deep learning. The method utilizes low- and high-noise X-ray CT reconstruction images acquired with different scanning times as training data to create a model to remove noise patterns from the reconstructions. This noise-reduction method is demonstrated using a battery and a plastic object as examples. We also present analysis results of these images and show that deep learning also improves analysis accuracy.

1. Introduction

X-ray CT is a technology that allows non-destructive three-dimensional observation and numerical analysis of samples. It is widely used in manufacturing, from research and development to quality assurance and failure analysis. Accurate analysis requires high-quality CT images, making the selection of X-ray energy, resolution, and scanning time crucial. Shorter scanning times increase image noise, which can compromise the accuracy of both visual observation and numerical analysis. However, especially in the fields of quality assurance and failure analysis, the number of samples processed per day and work efficiency (throughput) are often prioritized, requiring fast yet accurate evaluation. Because X-ray CT is frequently used for sampling inspection, improving efficiency to increase the number of samples is desired.

As a common approach to image quality improvement using deep learning, convolutional neural networks (CNNs)-based methods have been widely studied(1). In deep learning for CT images, models are typically trained on large amounts of data to learn noise characteristics and structural features of CT images(1). CNNs can hierarchically extract local spatial features, enabling effective separation of complex noise distributions from fine structural details in low-dose CT images. As a result, CNNs have attracted attention as a means of compensating for image degradation associated with high-speed scanning. However, in many studies, image quality improvements have been evaluated using image quality metrics, and the impact of such improvements on the accuracy of subsequent analyses has not been sufficiently studied(1),(2).

In this article, we evaluate how quality improvement of X-ray CT reconstruction images using deep learning affects analysis accuracy. In Section 2, we describe the training-data preparation method and the procedures for model training and inference. Inference in this paper means the process of applying a trained neural network model to make predictions or decisions on new, unseen data. In Section 3, we demonstrate image-quality improvements achieved by deep learning using a battery and a plastic specimen as examples. Furthermore, by comparing analysis results of the images before and after inference, we show that the accuracy of the analysis is enhanced.

2. Model Creation and Inference

2.1. Training data preparation

To train the deep learning model, reconstructed CT images of two quality levels were used: low-quality and high-quality images obtained from short- and long-time scans, respectively. These are referred to as “Teacher (coarse)” and “Teacher (fine).” A sequential set of reconstructed cross-sectional images is defined as a “CT dataset,” and these datasets were used as training data.

Two approaches, denoted as methods (A) and (B), were used to construct the model. In method (A), CT datasets from short- and long-time scans were used as Teacher (coarse) and Teacher (fine), respectively, with the same number of projections but different exposure times per projection.

In method (B), a single long-time scan was performed, from which a downsampled dataset and the full dataset were reconstructed and used as Teacher (coarse) and Teacher (fine), respectively. This approach requires only one scan and reduces the effect of sample drift between the two datasets.

A cylindrical battery and a plastic part were used as samples. Both samples required full inspection, quick scanning, and quantitative numerical analysis. For batteries, it s necessary to quantitatively analyze, in a short time, the length of the “overhang,” which

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is provided to prevent "winding misalignment" that can cause an internal short circuit and subsequent fire. For plastic parts, full inspection of the surface area is required for quantitative evaluation of molding defects, such as flash, sink marks, or surface roughness.

Models were created using method (A) for the battery and method (B) for the plastic object. The creation conditions are shown in Table 1. For the battery, a CT dataset acquired over 4 minutes was used as Teacher (coarse), and a dataset acquired at the same position over 17 minutes was used as Teacher (fine). For the plastic part, 2,400 projection images were acquired and reconstructed by downsampling them at regular intervals to 120 images. The reconstructed data were used as Teacher (coarse). The reconstructed data created with all 2,400 images were used as Teacher (fine). Section 3 shows the images along with the results of the inference performed using the created models.

2.2. Model Training

For this deep learning model, we used a common two-dimensional DnCNN (denoising convolutional neural network)[(2)–(4)]. The training process of the model is shown in Fig. 1. During the model training, initially, a 10-layer convolution and batch normalization kernel is applied to the Teacher (coarse) to estimate the noise image. The kernel is then refined so that the results obtained by subtracting the noise image from Teacher (coarse) are closer to Teacher (fine). By repeating this cycle, a model capable of removing noise patterns can be obtained. In this study, the iterative calculation was performed for 20 epochs.

Table 1. Model creation conditions.

Sample	Method	Teacher (coarse)	Teacher (fine)
Battery	(A)	4-minute scan	17-minute scan
Plastic part	(B)	120/2,400 frames reconstruction	2,400/2,400 frames reconstruction

2.3. Inference

In inference, a post-inference dataset after subtracting estimated noise is produced, when the trained model (kernel) is applied to the input pre-inference dataset.

Table 2 shows the subjects of inference for each sample. For the battery, the same data (four-minute scan), as Teacher (coarse), was used as the subject of inference. For the plastic object, new data was captured at 2, 4, 8, 15, and 30 minutes, of which only the 2-minute data was used as the subject of inference.

The time required for inference using a pre-trained

Table 2. Subjects of inference for each sample.

Sample	Method	Subject of inference
Battery	(A)	4-minute scan data
Plastic part	(B)	2-minute scan data

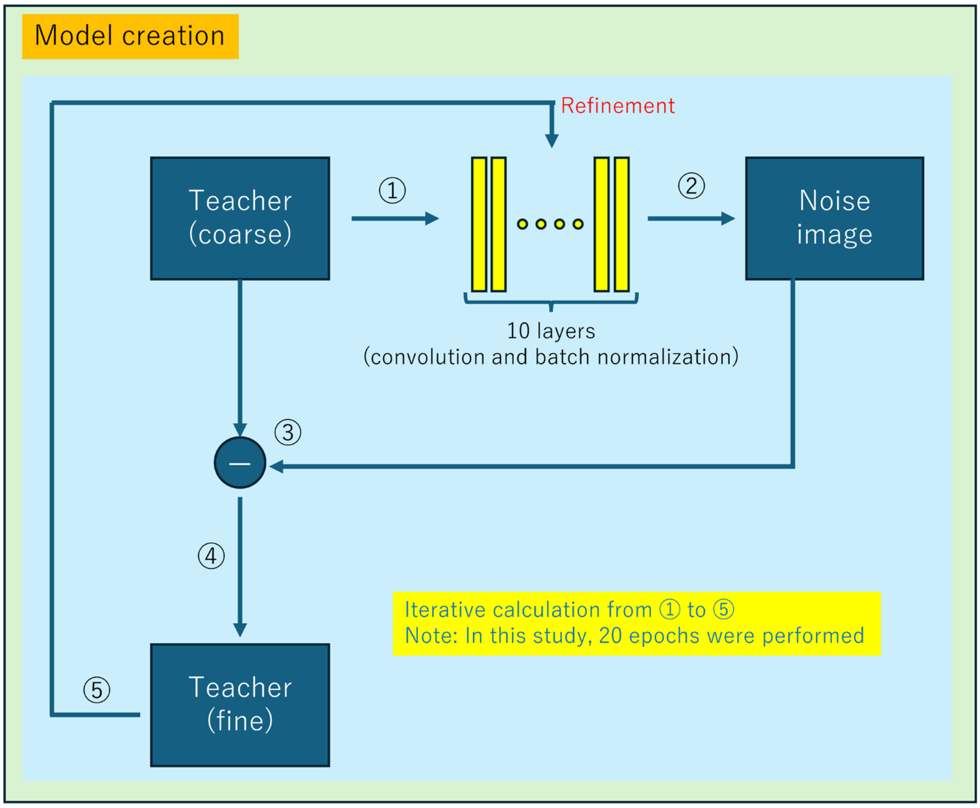

Fig. 1. Model creation.

model ranges from a few seconds to a few minutes. The dataset used for inference can be acquired under conditions similar to those of Teacher (coarse), which makes this deep learning method highly practical and easy to use.

3. Evaluation Method and Results

3.1. Battery

For the battery, we prepared pre-inference data, Teacher (fine), and post-inference data, and compared the CNR (contrast-to-noise ratio) between the cathode and air in each image. Furthermore, we conducted a quantitative shape analysis of the electrode overhang.

Table 3 shows the CNR values, and Fig. 2 shows the images used for the comparison. In the obtained post-inference data, noise was significantly reduced compared to the pre-inference data. The CNR improved sevenfold after inference and reached values five times higher than Teacher's (fine). As a result of the improved CNR, a clearer separation between the battery's anode and cathode can be observed. This is also clearly seen in the line profile along segment AB in Fig. 2.

Table 3. Comparison of CNR of the battery.

	Mean (Cathode)	Mean (Air)	Std Dev (Air)	CNR
Pre-inference	26,551	18,196	1,622	5.2
Teacher (fine)	24,273	16,764	988	7.6
Post-inference	37,691	24,273	351	38.2

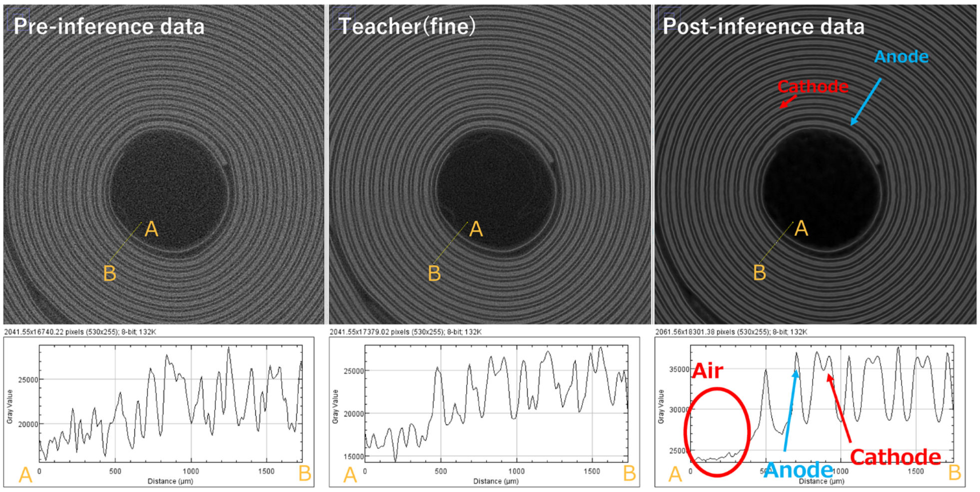

Fig. 2. Comparison of CT tomograms of the battery.

Table 4. Comparison of battery overhang length.

Data	Overhang length (mm)
Pre-inference data	0.64
Teacher (fine)	0.59
Pre-inference data	0.59

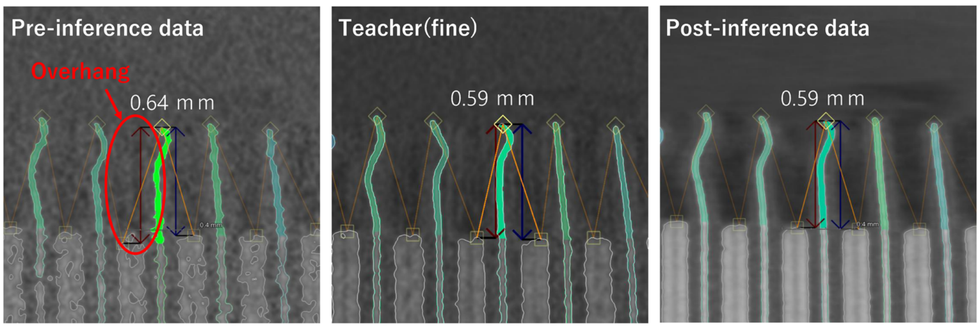

Fig. 3. Battery overhang analysis.

The results of the overhang analysis conducted on these data are shown in Table 4. The overhang length of the inference data shows the same value as that of Teacher (fine). This improvement is attributed to the removal of noise components of Teacher (coarse) by inference, allowing the electrode shape to be extracted more clearly, as shown in Fig. 3. It should be noted that Teacher (coarse) was acquired in 4 minutes, while Teacher (fine) was acquired in 17 minutes. This means that the analysis accuracy of data acquired in 4 minutes was improved to a level comparable to that of data acquired in 17 minutes through inference. In other words, by using deep learning, we can expect to reduce the scanning time to approximately one-fourth while maintaining the analysis accuracy.

3.2. Plastic object

For the plastic object specimen, CNR between the sample and air was compared among Teacher (coarse), Teacher (fine), and the pre- and post-inference images acquired by two-minute scanning. Furthermore, we compared the calculated surface area for multiple sets of image data acquired under different exposure time conditions, as well as for inference data acquired by short-time scanning (two minutes), to verify the accuracy improvement by the inference.

Table 5 shows the CNR values, and Fig. 4 shows the images used for comparison. For the post-inference images acquired with 2-minute scanning, the CNR improved by 28 times compared to the pre-inference images and was six times higher than that of Teacher (fine).

Table 6 shows the results of the surface area calculation for the pre-inference data (2, 4, 8, 15, and 30 minutes), the post-inference data acquired with a 2-minute scan, and Teacher (fine). In this comparison, the value of Teacher (fine) is assumed to be the true value of the surface area. We confirmed that the longer the scanning time, the closer the pre-inference surface area was to the true value. Meanwhile, the surface area accuracy of the data acquired by the 2-minute scan was significantly improved by inference, yielding a value close to the true value (Fig. 5).

Figure 6 shows the 3D images of the two-minute scan data pre- and post-inference. In the post-inference data, the surface roughness observed in the pre-inference data was reduced, which is considered to have contributed to the decrease in surface area and the improvement in analysis accuracy. Since the scanning time (exposure time) for Teacher (fine) is 40 minutes in this case, we expect that deep learning will allow the scanning time to be reduced by a factor of approximately 20 while maintaining the same level of analysis accuracy.

Table 5. CNR comparison of the plastic part.

Data	Mean (Sample)	Mean (Air)	StdDev (Air)	CNR
Teacher (coarse)	53,390	11,113	4,722	9.0
Teacher (fine)	53,771	11,082	953	44.8
2 minutes Pre- inference	56,515	11,802	4,230	10.6
2 minutes Post- inference	53,699	14,253	141	280

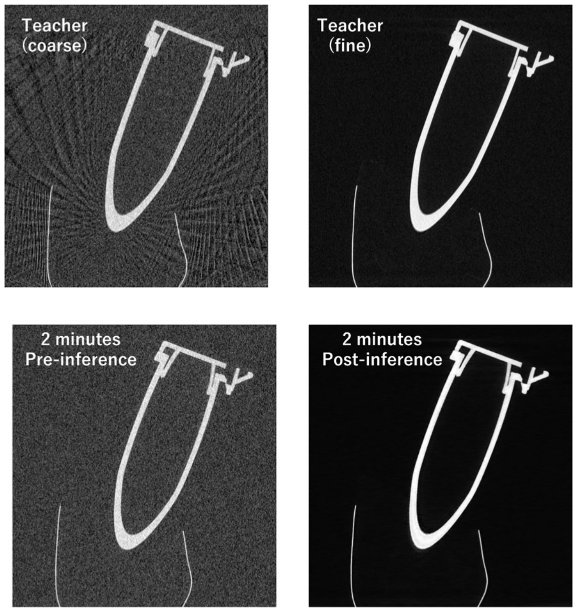

Fig. 4. Comparison of CT tomograms of the plastic part.

Table 6. Surface area of the plastic part.

Scanning time	Surface area (mm^2) Pre-inference	Surface area (mm^2) Post- inference
2 minutes	2,956	2,821
4 minutes	2,895	—
8 minutes	2,849	—
15 minutes	2,838	—
30 minutes	2,833	—
Teacher (fine)	2,836	—

4. Conclusion

In this article, we explained a method for improving the image quality of X-ray CT reconstruction images using deep learning. We described the procedure using short-scan (coarse) and long-scan (fine) X-ray CT reconstruction images as training data for developing a noise-removal model.

Using a battery and a plastic object as examples, we showed that the image quality of X-ray CT reconstruction images acquired by short-time scanning can be improved by deep learning. We also presented examples of analyses for these images and reported that the analysis accuracy was improved by deep learning.

In the examples presented in this article, the same CT instrument was used for both training and inference.

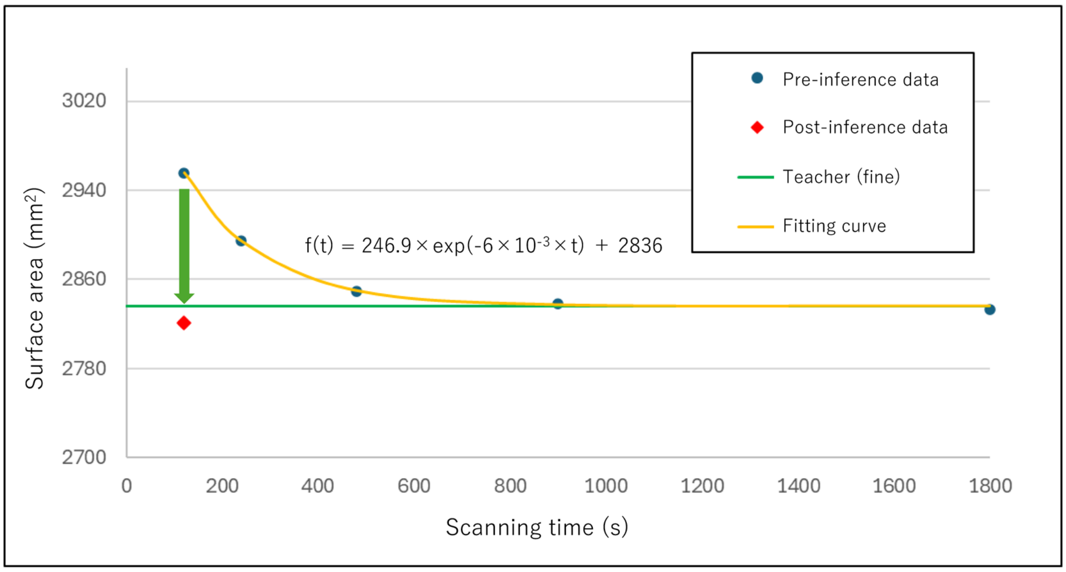

Fig. 5. Plot of the surface area vs. scanning time for the plastic object.

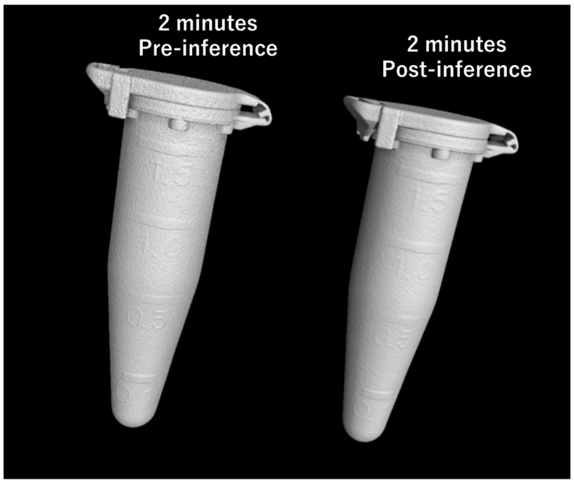

Fig. 6. Comparison of 3D images pre- and post- inference.

However, this is not necessary since deep learning is expected to generalize well to similar samples. For example, one can use synchrotron data to train a model and use it for inference of data acquired with other CT instruments. This method may improve the quality of the data obtained in laboratories or manufacturing facilities to be comparable to that of synchrotron facilities. Additional applications are currently being prepared for future publications and presentations.

References

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