BL47XU
Micro-CT

1. Introduction

BL47XU, which is an X-ray undulator beamline, is dedicated to micro/nano-CT and high-speed X-ray imaging. Those experiments need a high-flux-density monochromatic beam. To handle the high heat load of the undulator, a liquid-nitrogen (LN_2) cooling system is used to cool the monochromator crystals. The available energy range is between 6 keV and 37.7 keV with a Si (111) reflection of the monochromator. To eliminate higher harmonics, a set of reflection mirrors (double bounce in the vertical direction) can be inserted.

The beamline has two experimental hutches (EH1 and EH2) located just after the optics hutch. EH1 contains experimental tables for X-ray micro/nano-CT, while EH2 contains some X-ray optics and X-ray image detectors for nano-CT. Half of EH2 can be used as an open hutch for users who bring their own special equipment. In FY2022, a micro-laminography system for platelike specimens was installed and used for user's experiments. In addition, some image processing techniques have been evaluated. The details and some results are described here.

2. Introduction of micro-laminography system

A new laminography system was constructed in EH2. The main aim of this system is to obtain precise 3D images of relatively large or heavy samples that are oversized for the micro/nano-laminography system in EH1.

The photograph of the laminography system is shown in Fig. 1. The system has motorized X and Z linear motion stages and a precise rotation stage.

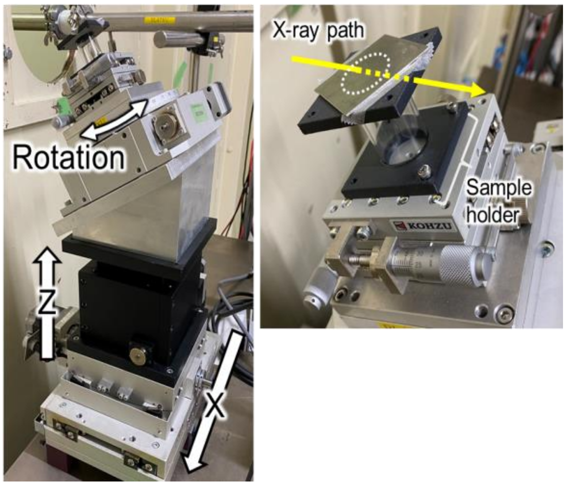

Fig. 1. Whole view of micro-laminography stages and close-up of sample holder.

The tilt angle of the sample rotation axis is set to 30 degrees. Manual X,Y linear motion stages are installed on the rotation stage for centering the sample. We also prepared optimized sample holders for this system. The experimental table has open space to set additional instruments such as charging/discharging control devices. This makes it easier to conduct in-situ measurements, such as applying an external field in the laminography system.

In the basic setup, the beam monitor has a sCMOS camera with 4096×3008 pixels. The field of view is ~1.5 mm×1.2 mm. The pixel sizes are ~400 nm and ~800 nm (2×2 binning). The magnification can be changed by replacing the objective lens of the beam monitor.

Figure 2 shows an example of a slice image of a thick section of brecciated rock (~30 mm×20 mm×5 mm) obtained using this system. The X-ray energy used was 30 keV. A single scan of 3000 projections for 360 degrees takes ~10 minutes with 100 ms exposure time. We can clearly observe the small fragments with cracks and small pores inside them. As shown in Fig. 2, it is very useful to understand the internal structure of a flat sample with up to submicron-scale texture in a large sample.

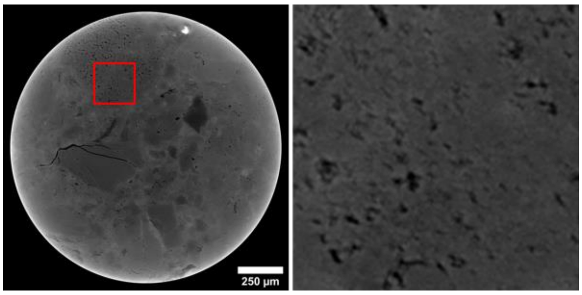

Fig. 2. Slice image obtained by new laminography system and magnified image of red square in the left image.

3. Introduction of deep-learning-based postprocesses

In recent years, deep-learning techniques have rapidly improved, and some of them are already applied in image processing techniques. We introduced such software for X-ray imaging experiments at BL47XU. The details of deep-learning-based postprocessing are described in this section.

3-1. Noise2Inverse noise reduction method

The deep-learning-based noise reduction method, Noise2Inverse [1], was evaluated.

This method requires only a dataset produced by the normal CT scan protocol; no additional data is needed. In the procedure, four sets of projection images made by splitting the projection images obtained by CT scan are used as training data.

We tested two types of neural network model in Noise2Inverse: U-Net and DnCNN. In the training of models, no time-consuming processes, such as hand painting of raw data, are needed. Although dependent on total data size, training time is about several hours for a single data set with about 1000×1000×1000 pixels. Figure 3 shows the result of noise reduction by Noise2Inverse and Gaussian filtering (2×2×2). Figure 4 shows histograms of X-ray linear absorption coefficient (LAC) values of images in Fig. 3. These results show that Noise2Inverse by both U-Net and DnCNN successfully reduces random noise. These images are less blurred than the Gaussian-filtered image. No distortion or fake texture was observed under normal CT scan conditions such as 2000 projections, 250 ms exposure, and 2000 pixels in width. However, we observed a small distortion of the image in the case where the number of projections was less than 1000 for the image width of 2000 pixels. In such a case, only 250 projections are used to reconstruct a single set of training data;

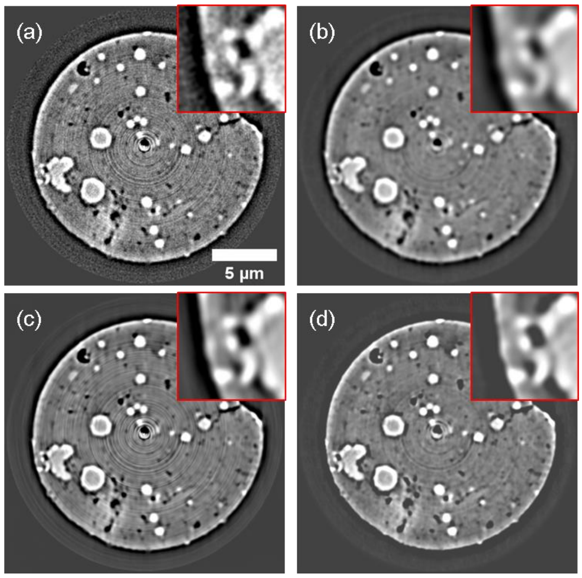

Fig. 3. Slice images processed by various methods. (a) CBP method only. (b) Applying Gaussian filter. (c) Applying Noise2Inverse (U-Net). (d) Applying Noise2Inverse (DnCNN).

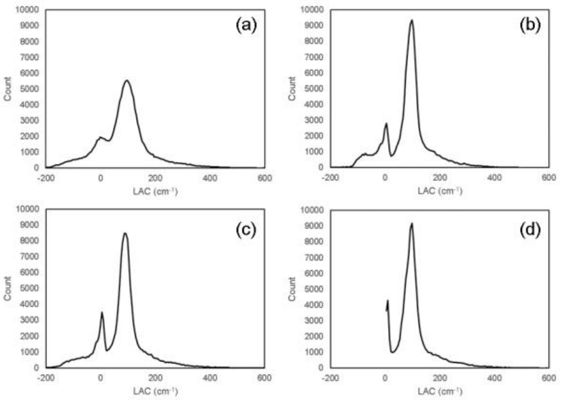

Fig. 4. Histograms of LAC values of each image in Fig. 3. In the case of DnCNN, the negative values were reset to 0.

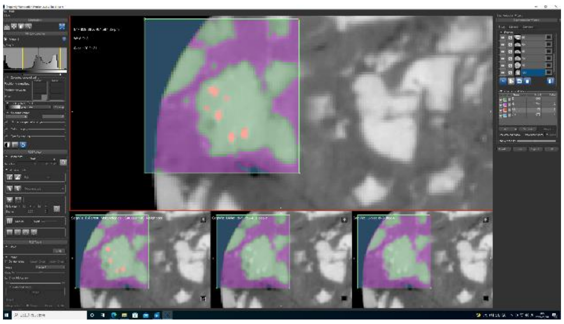

Fig. 5. Sample of segmentation procedure. Upper image is manually processed training data. Lower row shows the results of the first prediction using three learning models.

this is too sparse to reconstruct the image precisely, especially in the outer region of the image. There is no significant shift of LAC in the course of processing. However, a slight shift of LAC was observed in the case of DnCNN.

3-2. Deep-learning-based segmentation method

The image processing software Dragonfly (Comet Technologies Canada Inc.) was introduced at BL47XU. This software enables us to conduct image segmentation assisted by machine learning and deep learning.

To conduct segmentation, we must prepare some training data, that is, manually painted images, to separate phases. About 30 manually processed slices are necessary for the first learning. Figure 5 shows a snapshot of the segmentation procedure. We can conduct the learning by multiple methods for training datasets simultaneously. If the quality of the prediction is poor, we can manually edit the result of the prediction to improve the quality in the next learning.

Although this method requires the preparation of training data, machine-/deep-learning assistance reduces the cost of segmentation a lot compared with that of the traditional method where all images must be edited by hand painting. Not only segmentation processing but also many other functions are installed in Dragonfly software. More information is available on the official website [2].

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References

[1] Hendriksen, A. A. *et al.*, (2020). *IEEE Transactions on Computational Imaging*, **6**, 1320-1335.

[2] https://www.theobjects.com/dragonfly/index.html