1P2-8

Improving the accuracy of ultrasound CT images using CNN

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1. Introduction

Wooden buildings are susceptible to deterioration over time due to pests and weather, and cultural heritage structures have suffered considerable damage. Damaged buildings are repaired, but ideally, repairs should be kept to a minimum, as it is desirable to preserve the original appearance as much as possible. Therefore, non-destructive testing is necessary to accurately determine the location and size of defective areas.

Computed tomography (CT) using ultrasound time-of-flight (TOF) data has been proposed as a conventional method[1)], and the CT image is reconstructed from the acquired TOF data using the Filter Back-Projection (FBP) method. This method has the problems of time-consuming data collection and inability to reconstruct images when data is missing.

In this research, we propose a method using U-Net, a type of Convolutional Neural Network (CNN), which enables highly accurate image reconstruction even when TOF data is missing.

2 Method

2.1 Ultrasound propagation simulation

In this research, ultrasound propagation simulations were performed using matlab and the k-wave tool box, and TOF data were generated from the obtained waveform data. A sinogram was created from the TOF data and used as input data for the proposed model. For the simulation of ultrasonic wave propagation, a wooden pillar with a diameter of 11 cm was assumed, and a defect area of 1.0 cm to 2.0 cm was set inside the pillar. The defect area was assumed to be a circular cavity, with a sound speed of 340 m/s in air and 2200 m/s in a wooden pillar. One ultrasonic transmitter and 64 receivers were placed at equal intervals on the circumference of the wooden pillar(**Fig. 1**).

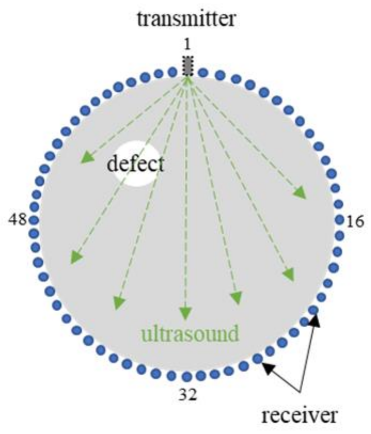

Fig. 1 Overview of ultrasonic simulation. (view of transmitter and receiver placement)

2.2 Network architecture

U-Net is a model for semantic segmentation developed for biomedical applications. **Fig. 2** shows overview of the Network architecture. Input missing sinograms to u-net and have it output reconstructed images. This U-Net model consists of an encoder on the left side that reduces the size of image data and a decoder on the right side that increases the size of image data. By linking the encoder's feature map to the decoder's feature map at each level, information from the encoder's large feature map is transmitted to the decoder side, making it easier to capture object location information. In **Fig. 2**, the gray arrow in the center corresponds to this feature map.

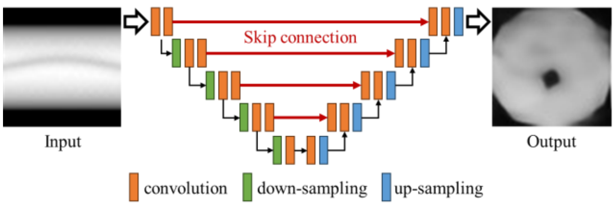

Fig. 2 Overview of the Network Architecture. Input missing sinograms to u-net and have it output reconstructed images.

3. Results and Discussion

Fig. 3 shows the results for (a) Input, (b) CNN, and (c) Ground Truth. Figure 3(b) shows the results when the sinogram without missing TOF is used as input. Figure 3(c) is the image reconstructed by the FBP method using (a) as input. Black areas in the reconstructed image

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indicate defect areas.

Fig. 4 compares of FBP and CNN reconstructed images for (a) 20, (b) 40, and (c) 60 missing data. The image reconstructed by the FBP method contains multiple linear artifacts even with a small number of missing data, making it difficult to see the abnormal areas, while the reconstructed image estimated using U-Net is able to estimate the location and size of the defect areas when the number of missing data is small.

4. Conclusion

In this research, we proposed a method for estimating reconstructed images from TOF data using a U-Net model. The proposed method was able to accurately estimate the reconstructed image by inputting TOF data to the U-Net model learned by natural images. In addition, even when incomplete TOF data with missing data was input, better output results were obtained than with the conventional method.

In the future, we aim to further improve the accuracy of the estimation, estimate the shape of anomalous areas with different shapes, and reconstruct images when using received waveform data obtained from actual equipment measurements.

References

1) Y. Tomikawa, Y. Iwase: K. Arita, and H. Yamada. Jpn. J. Appl. Phys. **24** (1984) 187

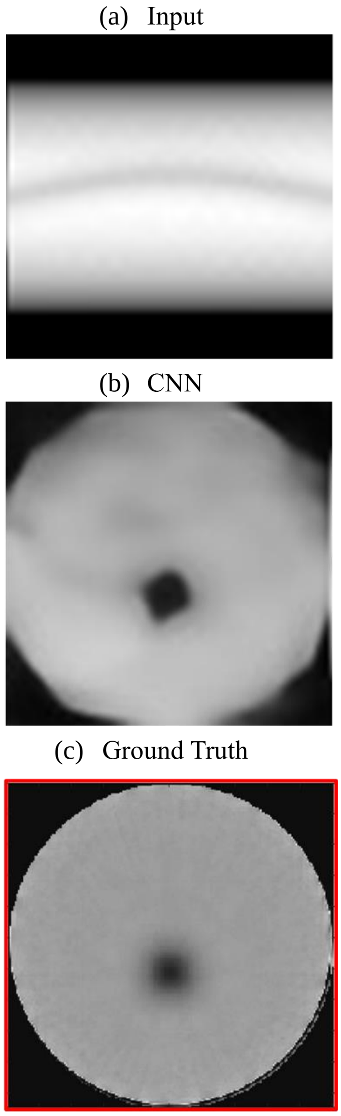

Fig. 3 Comparison of reconstructed images by (a) Input ,(b) CNN, and (c) Ground Truth

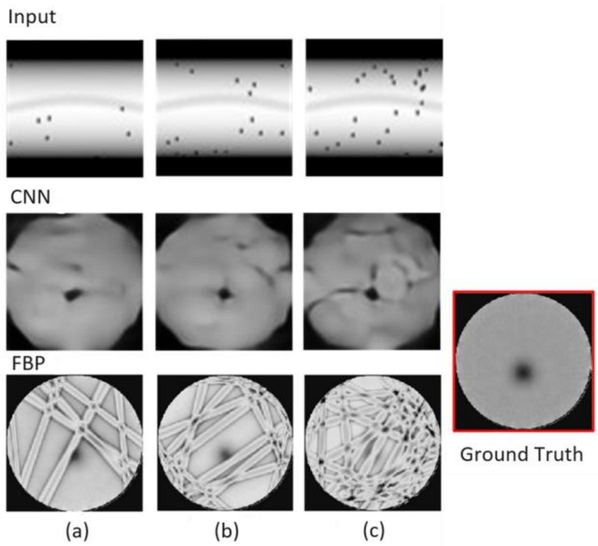

Fig. 4 Comparison of FBP and CNN reconstructed images for (a) 20, (b) 40, and (c) 60 missing data.