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High precision CT image reconstruction using deep learning based ultrasound propagation time estimates

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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.

Ultrasonic non destructive test for Wooden pillars has been improved by our experimental research and computer simulations[1]. To detect a correct size and position of a defect area, we think correct ultrasonic propagation time should be measured. We have proposed a method for estimating the correct propagation time, however, we have not reached the correct estimation of defects[1].

In this research, we propose a method to estimate the propagation time of ultrasound using deep learning and reconstruct high-precision CT images using the Filter Back Projection(FBP) method.

2. Methods

2.1 Ultrasound propagation simulation

In this research, simulations were performed using the numerical analysis software MATLAB2021b and the acoustic toolbox k-wave ToolBox [2].

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 3.0 cm was set inside the pillar. The defect area was assumed to be a circular cavity, with a sound velocity of 340 m/s in air and 2200 m/s in a wooden column. One ultrasonic transmitter and 64 receivers were placed at equal intervals on the circumference of the wooden pillar(**Fig. 1**). Ultrasonic waves were irradiated to towards the wooden pillar by an ultrasonic element of a source, and another ultrasonic elements as receivers acquire the sound pressure waveforms. The defect area on the wooden pillar are moved, and ultrasonic data are acquired each time.

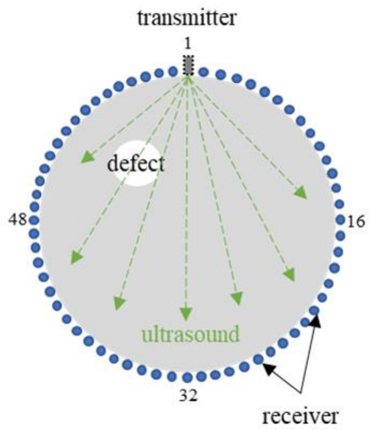

Fig. 1 Overview of ultrasonic simulation. (view of transmitter and receiver placement)

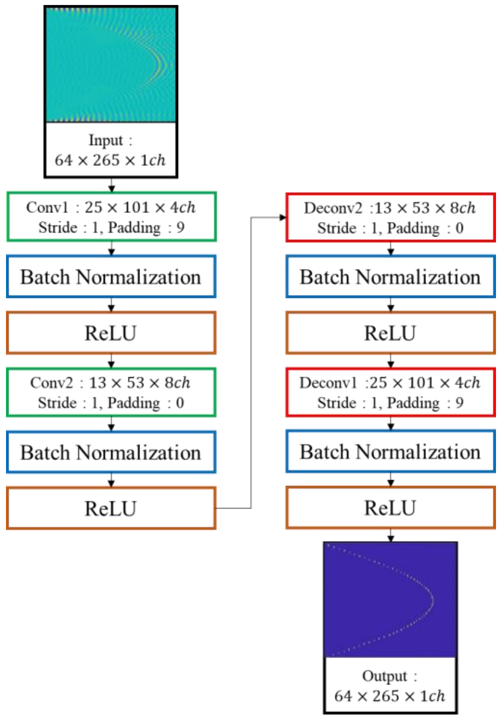

Fig. 2 Deep Learning Network Structure.

2.2 Network architecture

Figure 2 shows the network structure of the Convolution Neural Network (CNN) used in this research. It consists of a 2-D convolution layer, Batch Normalization, ReLU function, and 2-D

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Deconvolution layer(Fig. 2). The kernel size of Conv1 is [25x101x4ch] and Conv2 is [13x53x8ch], half the kernel size and twice the number of channels. The input data is the ultrasonic waveform obtained from the simulation. Input data size and number of channels are [64x265] and [1ch]. The number of training and test data was 900 and 64 respectively. The number of epochs is 600. The optimization algorithm utilized Stochastic Gradient Descent (SGD) and the Mean Squared Error (MSE) was used as the loss function.

3. Results and Discussion

Figure 3 compares reconstructed images by (a) conventional method, (b) deep learning, and (c) Ground Truth. FBP was used as the image reconstruction method. (a) Conventional methods use a threshold value to estimate the ultrasound propagation time. As shown in Figure 3, the CT image reconstructed using the ultrasound propagation time estimated by deep learning was more accurate than the CT image using the conventional method. The dark-colored areas in the reconstructed image represent defect areas, indicating that the deep learning-based method clearly shows defect areas.

Table 1 shows the evaluation values of conventional and deep learning methods using multiple image evaluation methods. Mean Squared Error(MSE), Peak Signal-to-Noise Ratio(PSNR), and Structural SIMilarity(SSIM) were used for image evaluation. The lower the value for MSE, the better the evaluation value; the higher the value for PSNR and SSIM, the better the evaluation value. As shown in Table 1, for all image evaluation methods, the Deep Learning method has better evaluation values than the conventional method.

Table. 1 MSE, PSNR, and SSIM evaluation values for conventional and Deep Learning methods.

	MSE	PSNR	SSIM
Conventional	2.871	25.184	0.992
Deep Learning	1.876	26.392	0.994

4. Conclusion

In this research, we validated the effectiveness of highly accurate CT image reconstruction based on ultrasound propagation time estimation using deep learning. The reconstructed images were quantitatively evaluated using several image evaluation methods (MSE, PSNR, and SSIM). As a result, comparing the results obtained under the experimental conditions and methods in this research, it was confirmed that the estimation method using deep learning produced higher evaluation values for all image evaluation methods and produced highly accurate CT images compared to the conventional method.

References

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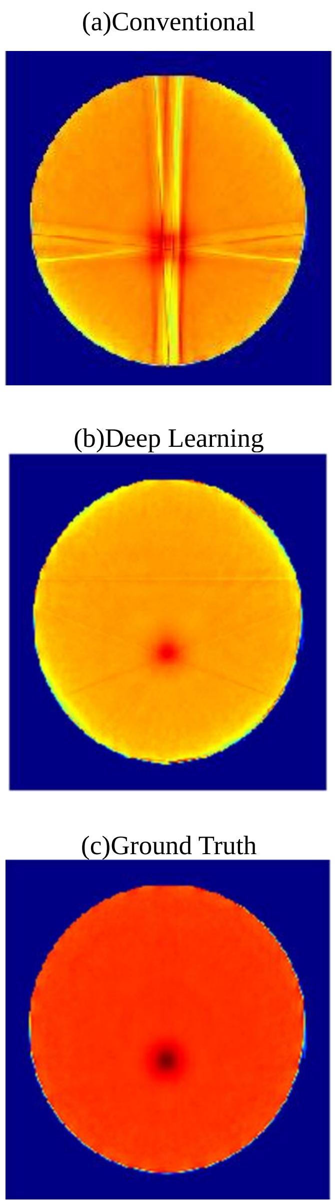

Fig. 3 Comparison of reconstructed images by (a) Conventional method, (b) Deep Learning, and (c) Ground Truth.