3P5-17

Study of Back Scatter Ultrasound Imaging Based on a Machine Learning Technique Using Numerical Simulation

機械学習を用いた超音波後方散乱波イメージングの数値シミュレーションによる検討

Shigeaki Okumura[1†], Yoshiki Nagatani[2], and Shuqiong Wu[3] ([1]R&D Dept., MaRI Co., Ltd.; [2]Dept. of Electronics, Kobe City Coll. of Tech., [3]Grad. School Inform., Kyoto Univ.)

奥村　成皓[1†]，長谷　芳樹[2]，武　淑瓊[3] ([1](株)マリ　研究開発本部, [2]神戸高専　電子工学, [3]京大院　情報)

1. Background

Several beamforming techniques have been proposed for high-resolution ultrasound imaging. However, the difference in propagation speed and complex structures of the propagation media deteriorate the quality of the imaging.

The machine learning, neural network, and deep-learning-based techniques have been widely used in several fields recently. Our group applied neural network-based methods for the quantitative ultrasound techniques which measure the strength and quality of bone[1] and the ultrasound two-dimensional geometry imaging techniques [2].

Both studies employ transverse transmission technique that requires the separated transmitter(s) and receiver(s) to measures the ultrasound signals that propagate along with the media. In this study, we apply the neural network-based imaging algorithm to the backscatter imaging technique, which places the transmitter and receivers on the same side and measures the backscattered signals from the target.

We investigate the performance of the proposed algorithm with the numerical simulation. The neural network-based techniques typically require a large number of training datasets. Thus, the simplified numerical simulation is suitable for the pilot study of the neural network-based techniques.

2. Materials and Methods

For the numerical simulation, we prepared 20000 two-dimensional (2D) geometries with the size of 128×64. To simulate the target with the complex structure such as the trabeculae of the cancellous bone, we placed rod-like reflectors randomly in the simulation field. The length was 16±8 px, the thickness was 3±2 px, and the range of rod angles was randomly selected from -45 and 45 degrees. The occupation ratio of the rod-like reflectors in the full simulation field was between 0 and 0.15. We

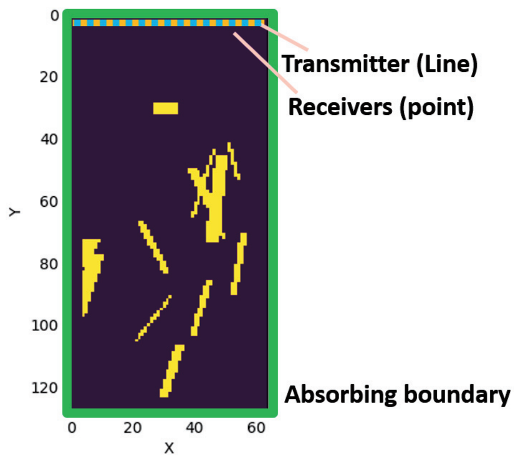

Fig. 1　Schematic illustration of the simulation setting. The line transmitter and point receivers are used.

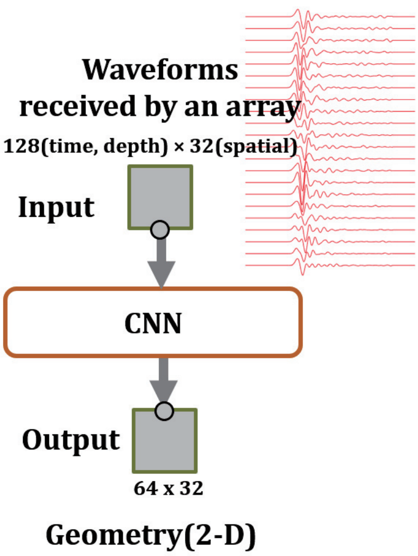

Fig. 2　Schematic illustration of the proposed algorithm for the imaging.

implemented the absorbing boundary condition at the four edges of the model.

Fig. 1 shows a schematic illustration of the simulation setting example of the simulation setting. We used the two-dimensional acoustic FDTD simulation. A single pulse of a sinusoidal wave was transmitted from a line transmitter. Then, the propagated waves were received at the 28 points that mimic the array receiver.

Fig. 2 shows a schematic illustration of the proposed imaging algorithm. We used the convolutional neural network (CNN). The pairs of the true 2D geometry and the waveforms were used for training. The input is waveforms, and the output is the 2D geometry. As the output, the shrank images with the pixels of 64×32 pixels were used. The numbers of data used for training and validation were 16000 and 2000, respectively and the remaining 2000 were used for testing.

3. Results and discussions

Figs. 3 and 4 (a) show the received signals at point receivers. We used the received signals as input. The estimation results (output images) are shown in Figs. 3 and 4(b). The true geometry is shown in Figs. 3 and 4(c). The estimated result shows a good agreement with the true geometry.

As shown in Figs. 3 and 4 (b), the quality of the output image depends on the Y-axis (depth) of the target. To investigate the performance of the proposed method, we separate the output result into four parts as shown in Fig. 3(b). The mean of the RMSEs of the four parts is shown in Fig. 5. The RMSE is lower than that of upper parts because the lower parts affected by the multiple reflections and refractions. The RMSE is calculated at the region of interest where the target can be existed.

The error also caused by the limited calculation step of FDTD. The higher number of time step should include more information of deeper part. However, it requires a higher calculation cost. Because this study is the pilot study for the backscatter imaging with CNN, the further evaluations and calculations are required as the future work.

3. Conclusion

In this study, we apply CNN-based imaging technique for the 2D ultrasound backscatter imaging. We succeeded in reconstructing the image and evaluated the performance. As the future work, we evaluate the algorithm with longer time step and modify the algorithm for the 3D imaging.

Acknowledgment
This study was supported in part by JSPS KAKENHI Grant Number 16K01431 from the Japan Society for the Promotion of Science.

References

1. Y. Nagatani, S. Okumura, and S. Wu, Proc. 2018 IEEE International Ultrasonics Symposium (IUS). IEEE, 2018.
2. Y. Nagatani, S. Okumura, and S. Wu, and T. Matsuda, JASA Express Letters 2019, submitted.

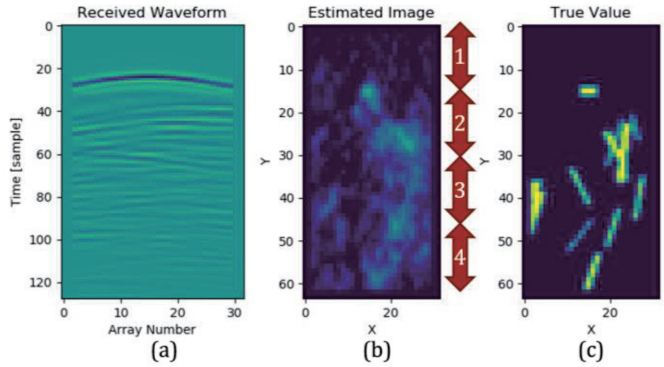

Fig. 3 (a)The received waveform (Input data), (b) estimation result of our proposed algorithm(output), and (c) true image. Double arrow shown in (b) represents the separated area for RMSE calculation.

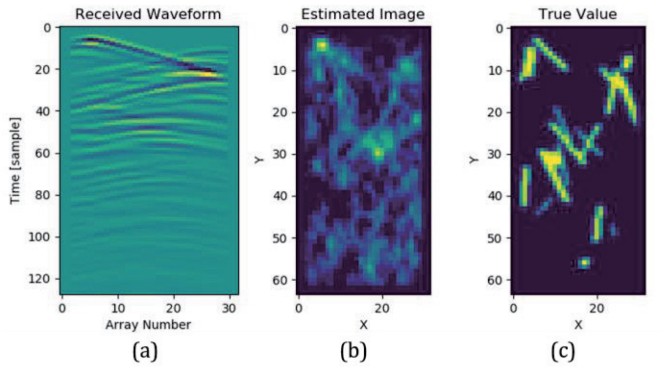

Fig. 4 Same as in Fig.3, but with another sample.

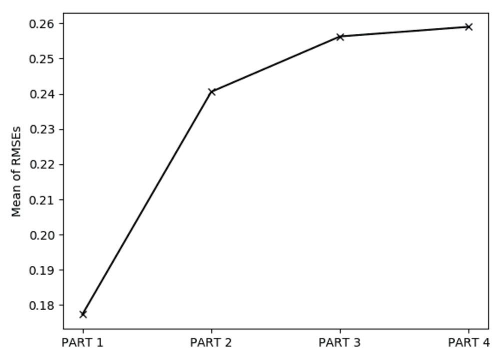

Fig. 5 Calculated RMSE at four different parts. The parts depend on the depth of the target.