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RF Data Recovery using Deep Neural Network in Subjects Including Bone for Ultrasound Computed Tomography

骨を含む領域における深層学習を用いた超音波 CT の RF 信号の復元

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1. Introduction

Currently, echo imaging is widely used as a medical imaging method due to its portability, low cost and spatiotemporal resolution. In recent years, USCT (Ultrasound computed tomography) has become a practical method. USCT acquires reflected wave as well as transmitted wave, which can reconstruct the image of medium sound speed and attenuation profile. And high spatial resolution can be archieved.

Greenleaf *et al.*[1] showed that sound speed and attenuation index could be used to distinguish benign masses from cancer by measuring the sound property in a breast. However, this method was not used as populer clinical imaging method due to the limited performance of computer in those days.

With the development of parallel computing methods in recent years, image reconstruction using USCT has become possible with practical accuracy and time. Duric *et al.*[2] developed the Computed Ultrasound Risk Evaluation (CURE) for the whole breast imaging system with high performance computing system. In this system, sound speed and attenuation profile in the breast is main target for diagnosis of breast cancer.

To expand the measurement object using USCT other than the breast, we aim to apply USCT with shadow-less imaging possibility to the orthopedic field. Shadow-less imaging has the possibility of quantitative evaluation of soft tissue in joint area. However, B-mode image for bone including huge artifacts caused by relrection at the bone surface.

In recent years, machine learning technology including deep learning has been developped. Deep neural network can have much capacity to be function for complex tasks.

In this study, we try to remove bone effects from RF data to enhance the previously mentioned advantages, and improve imaging quality by using Deep Neural Network (DNN). For training of the DNN, efficient development method combined with simulation was used.

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2. Method

2.1 RF recovery method

One way to reduce artifact is to apply DNN to reconstructed images, but we apply it to RF signal because it has much more information to distinguish a scattering wave of bone from the others. Schematic view of RF recovery was shown in Fig. 1. We adopt RF data received from the model including bone as input data, and the one received from the other model without bone as correct answer data for training DNN. Training data was created from the whole RF data by extracting small region corresponding to 10 pulses around the time of interest. U-Net architecture was used for the DNN and Mean absolute error was used as the loss function.

2.2 Generation of training data using wave propagation simulation

In general, DNN require 10,000 or more samples for training. Then, we generated training data by using simulation. Schematic view of medium for training data is shown in Fig. 2 and simulation configuration is shown in Table 1. By changing the diameter and position of bone model and wire positions, 75 pattern mediums were created. And small RF data corresponding to 10,000 points were extracted from the simulation results of the medium created. Wave propagation simulation was calculated by solving wave equation Eq.(1).

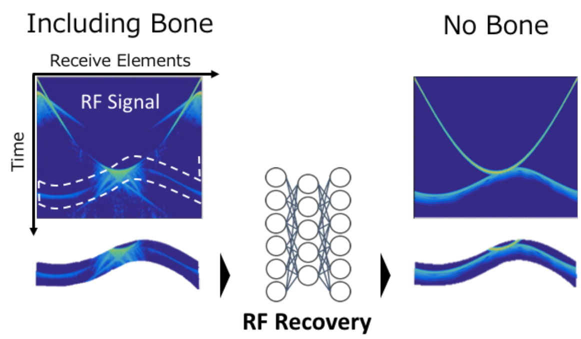

Fig. 1 Schematic View of RF recovery

Table 1. Simulation configuration

Diameter of the ring array	100 mm
Number of Receive elements	256
Center frequency	1.60 MHz
Sampling frequency	40.0 MHz
Density of water	1.00 kg/m^3
Density of bone model	1.91 kg/m^3
Sound Speed of water	1520 m/s
Sound Speed of bone model	2700 m/s

$$\frac{\partial^2 p}{\partial t^2} = c^2 \left(\frac{\partial^2 p}{\partial x^2} + \frac{\partial^2 p}{\partial y^2} + \frac{\partial^2 p}{\partial z^2} \right) \qquad (1)$$

p is sound pressure, c is sound speed of medium and t is time. As a simulator, MATLAB K-wave toolbox which solves Eq.(1) by pseudospectral time-domain method was used.

3. Results and Discussions

Figure 3 (a), (c), (d) shows the reconstructed images. In the case without bone, reconstructed image had no artifact. The one including bone had remarkable artifacts. On the other hand, even the case including bone, the one applied RF recovery had no artifact from the bone and its image quality was improved. In this study only one transmission element was used, then shadow area of the bone hide the wire. When multi transmitter RF data is used for DNN training, it is thought that the system can realize not only RF signal recovery but also perfect shadow-less imaging.

In this example, bone image was removed with artifacts. This effect seems to be derived from training data selection criteria. The reason for this is considered that training data was acquired from around wire region and no wire region, not including much data around bone border region.

This simulation study is for concept demonstration of proposed method. As a next theme of this simulation study, verification with actual equipment can be considered. We plan to apply fine tuning and use learning results in simulation for learning with actual machine data.

4. Summary

The effect of RF Data Recovery using Deep Neural Network in Subjects Including Bone for Ultrasound Computed Tomography was confirmed. The artifacts were suppressed and the images of wires were improved. The wires in the shadow region of the bone cannot be imaged but this problem will be solved by using multi-transmission information.

References
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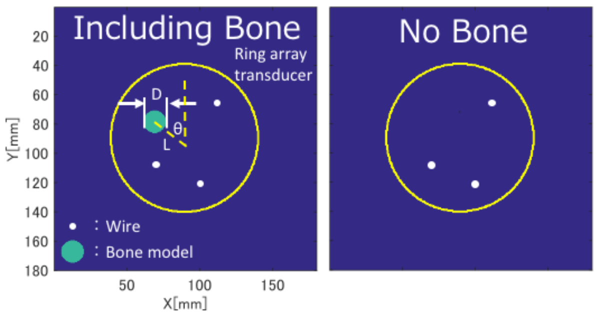

Fig. 2 Schematic View of medium

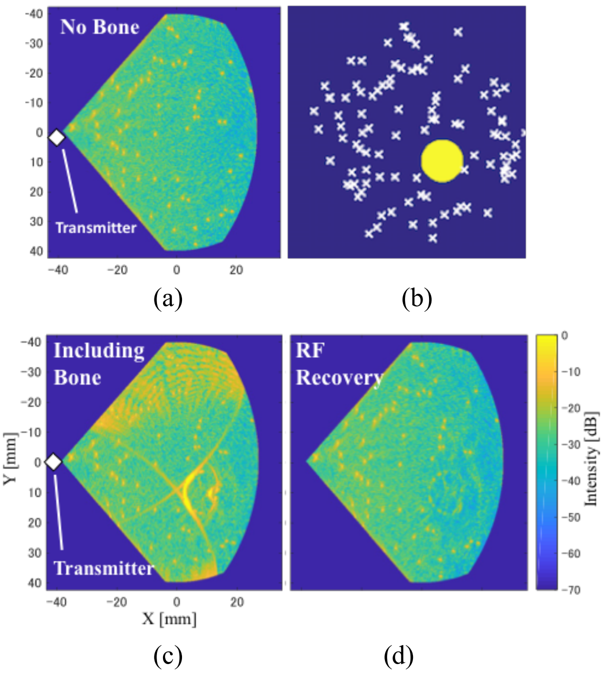

Fig. 3 Comparison of B-mode images
(a) No Bone (b) schematic view of the medium (c) Including bone condition (d) Including bone condition and RF recovery and applied