Preliminary investigation on deep learning for fast adaptive beamforming

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1. Introduction

Medical ultrasound systems are a modality that plays an important role in clinical practice. Beamforming is necessary to obtain ultrasound images. Generally, delay-and-sum (DAS) beamforming is used in clinical scanners. To obtain higher resolution, minimum-variance (MV)[1,2] beamforming was devised as an adaptive beamformer. However, an MV beamformer is more computationally expensive than a DAS beamformer and requires a longer execution time.

In this study, a convolutional neural network was designed using signals beamformed with DAS as input and those obtained with MV as output (teacher data). Since the convolutional operation is computationally less expensive than the matrix computation required for the MV method, we believe that it has the potential to achieve the same level of image quality as the MV beamformer at a short computation time.

2. Methods

The training data for deep learning was obtained by distributing ultrasonic scatterers using the ultrasound simulation program Field II[3,4] and constructing a virtual phantom to simulate ultrasound transmission and reception. The parameters of the simulation were set so that a linear array probe with a center frequency of 7 MHz was simulated, and the scatterer number density was set at 250 mm^{-2}. DAS beamforming and MV beamforming were performed on the received RF signal, and the profiles after respective beamforming were obtained. The covariance matrix was estimated by the method developed in our previous study.[5] In the human body, there are organs and lesions with various shapes. Therefore, an imaging method should be robust against the variation in target shapes, and the model needs to be trained with diverse data as much as possible. Therefore, the amplitudes and positions of hyper- and hypo-echoic cysts and point targets were randomly distributed in the training data. This was done because this would contribute to more effective predictions for unknown data. Examples of the actual training data generated are shown in **Fig. 1**.

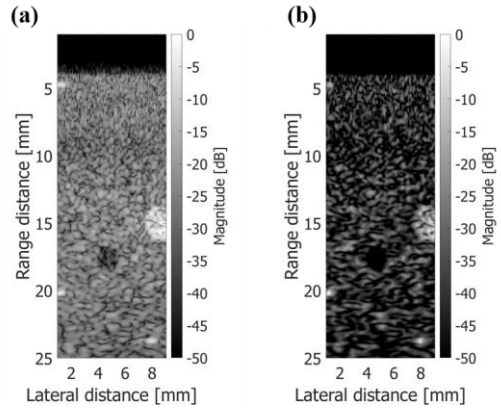

Fig. 1 Example images of (a) input data and (b) teacher data.

Since the number of images required for deep learning varies depending on the quality of the data used for training and the complexity of the problem, the learning curve method[6] was used to determine the preferred number of training data for this study as 1000 images. The Adam optimizer[7] was used to optimize the model, and experiments were conducted with an initial learning rate of 0.0005, batch size of 32, and number of epochs of 20.

A convolutional neural network (CNN) was used as the model in this study. The CNN structure used is shown in **Fig. 2**.

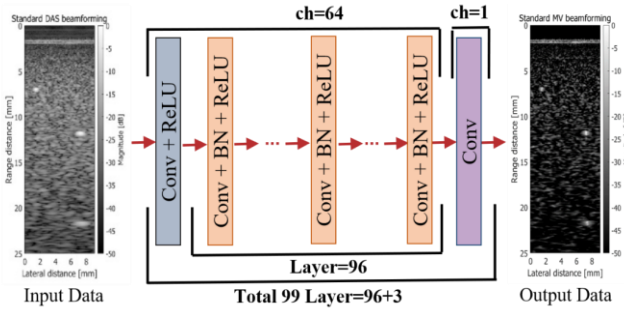

Fig. 2 Convolutional neural network architecture.

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The CNN consists of convolutional, ReLU, and batch normalization layers. The desired features are extracted by optimizing the weights and biases so that the two-dimensional response obtained by the convolutional filter is close to the correct data (teacher data). The ReLU layer has the advantage of rectifying the input signal and preventing gradient loss. [8] The batch normalization layer normalizes the output of each channel of the convolutional layer to speed up learning convergence and improve the learning rate.[9] The string and cyst phantoms were used as test data for evaluation. Phantoms were created under the same conditions as those used to generate the training data. B-mode images of the phantoms actually used are shown in **Fig. 3**.

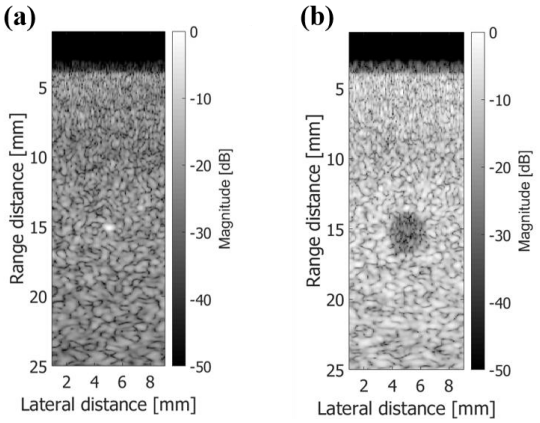

Fig. 3 Test data of string (a) and anechoic cyst (b) phantoms obtained by DAS beamforming.

3. Result

The B-mode images obtained with the conventional and proposed methods are shown in **Fig. 4.** The proposed method shows improved contrast and also cyst and speckle patterns similar to those in the MV images. For comparison of the image quality of the proposed method, quantitative evaluation metrics on DAS, MV, and proposed method are shown in **Table I**.

Table I Image quality among DAS, conventional MV, and proposed methods.

	DAS	**MV**	**proposed**
Contrast [dB]	-3.03	-0.34	-0.52
CNR [dB]	3.37	-3.30	-4.07
lateral FWHM [mm]	0.59	0.17	0.13
Time [s]	10.96	689.61	12.15

Contrast[10], contrast-to-noise ratio (CNR)[11], and full width at half maximum (FWHM) were used as evaluation indices. Contrast and CNR were calculated from the low-echo and speckle regions in the cyst phantom, and FWHM was calculated from the point spread function. The computation time was also compared among DAS and MV beamformers and proposed method.

The proposed method shows similar values for most of the indices to MV, indicating that it is able to reproduce images obtained with MV with significantly shorter computation time than MV.

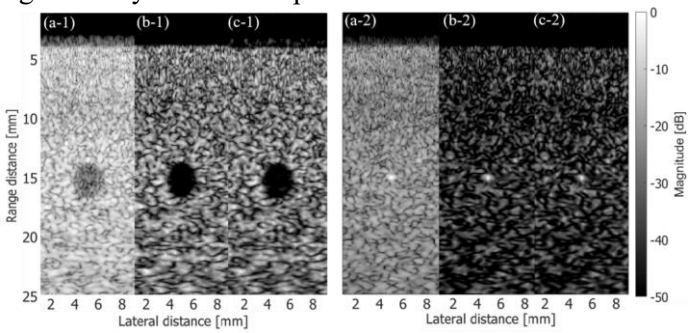

Fig. 4 B-mode images of the anechoic cyst (left) and point target (right). (a) DAS. (b) MV. (c) Proposed method.

4. Conclusion

In this study, we investigated the use of deep learning to accelerate the MV beamforming. The proposed method reduces the computation time while maintaining the same image quality as the MV beamforming method, suggesting that it can be applied to other image quality enhancement methods.

In the future, we plan to conduct validation experiments using actual phantoms and to verify the effectiveness of the proposed method when the properties of the training data are varied.

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