

## Visualization of blood flow by clutter filtering based on deep learning

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### 1. Introduction

Blood flow imaging is an important function in diagnostic ultrasound imaging. In ultrasound flow imaging, a clutter filter is required to suppress clutter signals from soft and hard tissues because echoes from blood cells are significantly weaker than these signals. In recent years, the singular value decomposition (SVD) based clutter filter is better than the traditional clutter filters in suppressing clutter signals. The excellent performance of the singular value clutter filter is due to its adaptive nature making it perform well in the entire cardiac cycle. Recently, deep neural networks have been used for various tasks because of their highly adaptive properties.

In our previous study, a preliminary study of clutter filtering using deep neural networks was investigated, and the results successfully visualized the weak echoes of the blood cells<sup>1,2</sup>. The contrast of the deep learning filter is higher than that of the SVD filter. In this present study, we increased the training data and successfully visualized the blood flow.

### 2. Methods

#### 2.1 Experimental data

In the present study, ultrasonic echoes from the carotid arteries of a 46-year-old and a 25-year-old healthy male were analyzed. A 7.5-MHz linear array probe (UST-5412, Hitachi) was used for transmitting and receiving ultrasonic signals with a custom-made ultrasonic acquisition system (RSYS0016, Microsonic). The pulse repetition frequency was 10417 Hz. Four sets of 10,000 frame data were prepared. The ultrasonic RF data and SVD data (the RF data filtered by SVD clutter filter) of the 46-year-old healthy male, the ultrasound RF

data and SVD data of the 25-year-old healthy male, used as input data, teacher data, input data for prediction, the data of comparison with the predicted data, respectively.

#### 2.2 Clutter filtering using deep learning

The long short-term memory (LSTM) neural network was used in this study. The network consists of one input layer, 200 of LSTM layers, a fully connected layer and a regression layer. The learning rate was set at 0.01 and the epoch set at 4.

The 10,000 frames of input data and teacher data were used for training. Therefore, the maximum of the length  $N_t$  of each sequence was 10,000. Each 2D B-mode image was composed of  $(N_x = 121) \times (N_z = 1309) = 158,389$  sampled signals. Those 158,389 sequences  $\mathbf{S}$  were standardized when they were used for training the neural network as shown below

$$\mathbf{S}' = \frac{\mathbf{S} - \mu}{\sigma}$$

$\mu$  and  $\sigma$  are the mean and standard deviation, respectively of data  $\mathbf{S}$ , and the standardized RF data  $\mathbf{S}'_{RF46}$  and  $\mathbf{S}'_{SVD46}$  are input into the network for training.

After obtaining the network, the standardized RF data of a 25-year-old male  $\mathbf{S}'_{RF25}$  was input into the network to predict the filtered  $\mathbf{S}_{pr25}$ .

#### 2.3 Evaluation of image contrast

The performance of the proposed method was assessed by evaluating the contrast of the obtained B-mode image. Contrast  $C$  was evaluated as

$$C = 20 \log 10 \frac{\mu_{blood}}{\mu_{tissue}} [\text{dB}]$$

where  $\mu_{blood}$  and  $\mu_{tissue}$  are mean gray levels in regions in a B-mode image corresponding to blood and tissue, respectively.

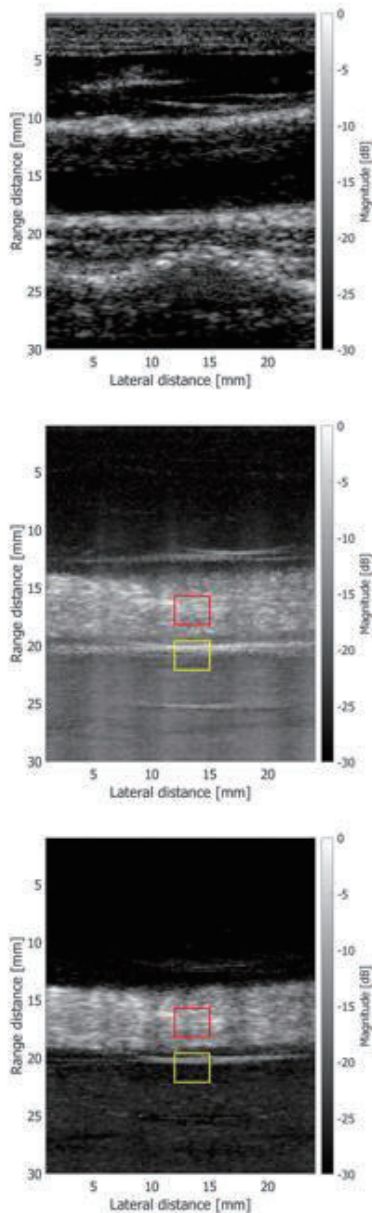


Fig. 1 Results of analyses of in vivo data from human carotid artery. (a) B-mode image from unprocessed signals. (b) B-mode image from SVD-filtered signals. (c) B-mode image from signals processed by deep neural network.

### 3. Result

In this study, we used a pair of data from the 46-year-old healthy male for training. Fig. 1(a) shows a B-mode image of a carotid artery of a 25-year-old healthy male before clutter filtering. By applying the SVD clutter filter to the RF signal, which composed the B-mode image in Fig. 1(a), the

clutter-filtered B-mode image was obtained as shown in Fig. 1(b). Also, Fig. 1(c) shows the B-mode image for the prediction of the deep learning clutter filter. Blood flow was successfully visualized. The red and yellow rectangles are the regions manually assigned as lumen (blood) and tissue for evaluation of the contrast between desired data  $S_{svd25}$  in Fig. 1(b) and predicted data  $S_{pr25}$  in Fig. 1(c).

The results of the contrast values are

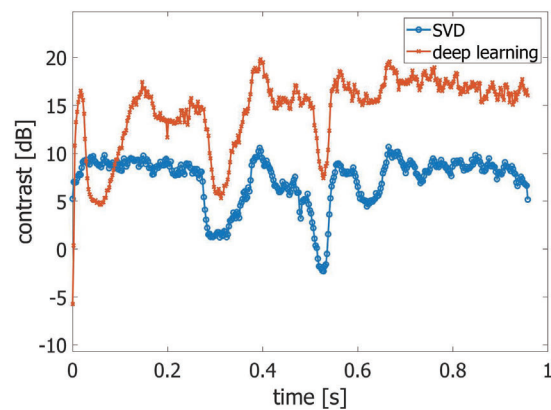


Fig. 2. Contrast values evaluated with respect to the data in Fig. 1.

shown in Fig. 2. From the images, the overall performance of the deep learning clutter filter is better than the SVD clutter filter.

### 4. Conclusion

In this research, the ultrasonic RF signal processed by a state-of-the-art clutter filter, i.e., SVD filter, was used as teacher data. The experimental data of the entire cardiac cycle was increased and successfully visualized the weak echo of blood flow in different cardiac cycles in different people. In our future work, we will investigate more efficient structures for deep-learning clutter filtering, and blood flow velocity estimation based on deep learning.

### References

- 1) H. Wang, S. Gao, M. Mozumi, M. Omura, R. Nagaoka, and H. Hasegawa: Proc. USE **41**, 1Pb5-1 (2020).
- 2) H. Wang, S. Gao, M. Mozumi, M. Omura, R. Nagaoka, S. Gao, Hasegawa, H: JJAP. **60** SDDE21 (2021).