

Study on speckle reduction of medical ultrasound images using deep learning with fully convolutional network

Fully convolutional networks による深層学習を用いたスペックル除去に関する研究

Kazuma Ando[†], Ryo Nagaoka and Hideyuki Hasegawa

(Graduate School of Science and Engineering for Research, University of Toyama)

安藤数真[†], 長岡 亮, 長谷川英之 (富山大院 理工)

1. Introduction

Speckle is a white dot-like pattern that is generated by interference of scatterers and reflections from tissues. Contrast and quality of ultrasound images are deteriorated by speckle. Hence, visibility of ultrasound images can be improved by speckle reduction. Smoothing filters such as Gaussian filter, median filter and non local means (NL-means)¹⁾ are methods used for speckle reduction. However, these methods cause loss of the characteristics details of tissues. It is assumed that optimal filter for speckle reduction is more effective to reduce speckle without losing the characteristics than smoothing filters. Therefore, in this study, we investigated the method for speckle reduction to optimize convolution layers using deep learning.

Moreover, it is assumed that a trained model requires low processing time because the amount of calculation for convolution is low and it can be accelerated using GPU. In this study, image quality of output results and processing time in each method are compared.

2. Method

In this study, ultrasound image speckle reduction is modeled as an optimization problem aiming to get a low speckle extent and high contrast image (\hat{x}) from the given speckle contaminated ultrasound image (x). The equation of the optimization problem is given as

$$\operatorname{argmin}_{\theta} \sum_i L(f_{\theta}(x_i), \hat{x}_i),$$

where f_{θ} is the neural network, θ is the parameters of f , and L is the loss function. L_2 loss $L(x, \hat{x}) = (x - \hat{x})^2$ is used for the loss function. This optimization problem is minimization of the difference between the outputs of neural network and the corresponding target data.

We used fully convolutional network (FCN)²⁾

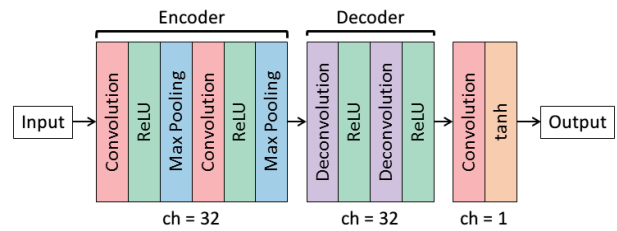


Fig. 1 Neural network architecture.

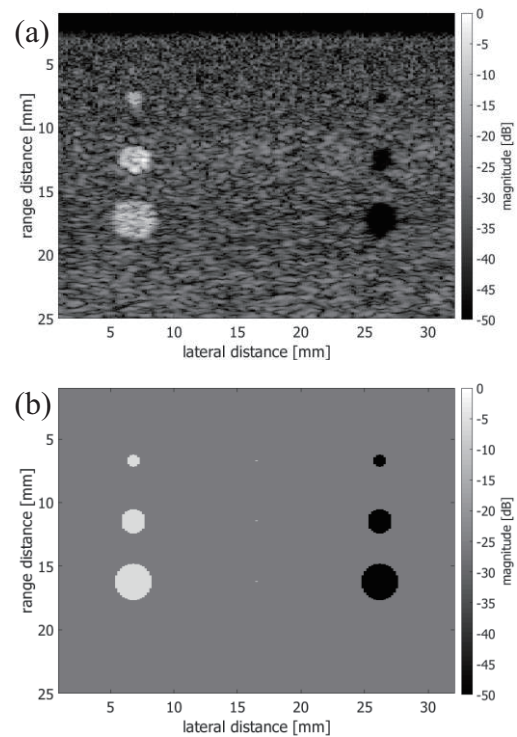


Fig. 2 Example images of (a) input data and (b) target data.

as neural network. The architecture of FCN used in this study is shown in **Fig. 1**. It contains encoder, decoder and a final convolution layer for the desired output. The encoder downsamples input data and extracts features. By contrast, the decoder upsamples extracted features. As shown in **Fig. 1**, the encoder contains two convolution layers and

max pooling layers. Similarly, the decoder contains two deconvolution layers. Each convolution and deconvolution layer, except for the final layer, has 32 channels and is combined with ReLU non-linearity as an activation function. The final convolution layer has 1 channel and tangent hyperbolic function. All convolution and deconvolution layers have 3×3 kernels and all max pooling layers have 2×2 kernels.

Sample images from input and target data used in this study are shown in **Fig. 2**. Target data is no speckle extent and high contrast images generated from scatterers. Input data is ultrasound images generated by simulation with distributed ultrasonic scatterers. The simulation parameters were set to linear array probe with a central frequency of 7.5 MHz and the density of scatterers was set to $79.26 /\text{mm}^2$. Field II^{3,4)} was used as ultrasound simulation program.

The optimization is performed using 512 pairs of input and target data, Adam optimizer⁵⁾ was used with an initial learning rate of 0.001, batchsize 32 and 4 epochs.

3. Result

Performance of the proposed method is compared with NL-means. NL-means parameters were set to search window 5×5 , similarity window 2×2 and standard deviation 10. To compare output results, carotid artery *in vivo* ultrasound data measured with a 7.5 MHz linear array probe was used as input. The input image and output results are shown in **Fig. 3**. It is shown that the proposed method reduces speckle and improves contrast. Furthermore, the speckle extent and contrast are measured using contrast-to-noise ratio (CNR) and contrast. The observed values are listed in **Table I**. As shown in **Table I**, the CNR and contrast values observed from the proposed method is higher than NL-means. Furthermore, the processing time of the proposed method is less than NL-means by 52.7 s. Therefore, it is concluded that the performance of the proposed method is better than NL-means.

4. Conclusion

In this study, we investigated the method for speckle reduction of medical ultrasound images using deep learning. The optimization is performed using FCN and pairs of input and target data generated by simulation. The proposed method performed better than the previous method in qualitative and quantitative performance evaluations.

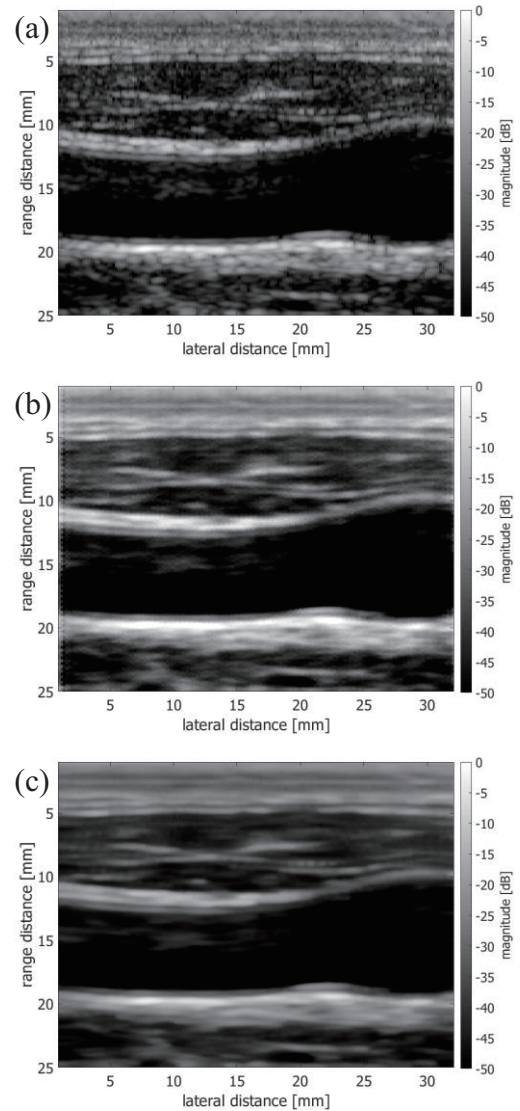


Fig. 3 Output images of (a) input, (b) proposed method and (c) NL-means

Table I Quantitative evaluation of speckle reduction methods

Method	CNR [dB]	Contrast [dB]
Input (no filter)	17.33	0.11
Proposed	19.37	2.58
NL-means	19.03	0.09

References

1. A. Buades, B. Coll and J. M. Morel: Proc. CVPR (2005) 60.
2. X. Mao, C. Shen and Y. Yang: Proc. NIPS (2016) 2810.
3. J. A. Jensen: Med. Biolog. Eng. Comput. **34** (1996) 351.
4. J. A. Jensen and N. B. Svendsen: IEEE Trans. Ultrason. Ferroelec. Freq. Contr. **39** (1992) 262.
5. D. Kingma and J. Ba: Proc. ICLR (2015) 1.