Domain adaptation in simulation model construction for classification of non-speckle region

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1. Abstract

Early detection of microthrombi circulating in the blood is required for prediction of venous thrombosis and comprehensive vascular function tests. The echoes from thrombus and alignment of blood cell may be observed as hyperechoic region (non-speckle component) in blood cell echo (speckle component), and can be identified by thresholding the envelope amplitude [1]. However, it is difficult to discriminate with non-speckle and speckle components when the change in brightness becomes obscure. One of the solutions is deep learning to improve the accuracy of a segmentation task of non-speckle components in blood echo. In our previous study, a learned model was constructed based on in silico data [2]. However, the learned model overfitted to the features of in silico data, and the incompatibility with the experimental data was a problem. In this study, we newly construct a method incorporating with adversarial learning and fine tuning, and aim to create a robust learned model that can also adapt to experimental data.

2. Training Data

Training data was supervised in silico data and unsupervised experimental data.

2.1. In Silico Data

Numerical simulation using Field II [3,4] was performed to simulate blood echoes containing non-speckle in the transmission and reception sound field of a 7.5 MHz linear probe and to create data with different number densities by increasing the number density of non-speckle components in stages. Scatterers imitating speckle and non-speckle components were randomly arranged at 30 points/mm^3 and at 0−25 points/mm^3, respectively. Based on our previous study, the scattering intensity ratio of speckle and non-speckle components was the minimum condition (speckle: non-speckle = 1:5) that shows stable discrimination accuracy [2]. Regarding the ground truth, the region of the maximum half width of envelope amplitude was set as 1, and the other region was set as 0, considering the point spread function.

2.2. Experimental Data

We measured the experimental data of blood mimicking fluid that contained non-speckle components in the speckle component such as in silico data. This fluid was made from nylon particles of a diameter of 40 μm (non-speckle component) with concentrations of 0 to 0.09% and particles of 10 μm with a concentration of 0.5% (speckle component). The number density of non-speckle components was about 0−25 points/mm^3, and the scattering intensity ratio (speckle: non-speckle) was assumed to be 1:10 from the theoretical formula.

3. Training Method

Fig. 1 shows an overview of the proposed learning method. U-Net [5] was used for the auto encoder (conventional method) and migrated with an adversarial learning in two phases (proposed method): auto encoder and discriminator [6].

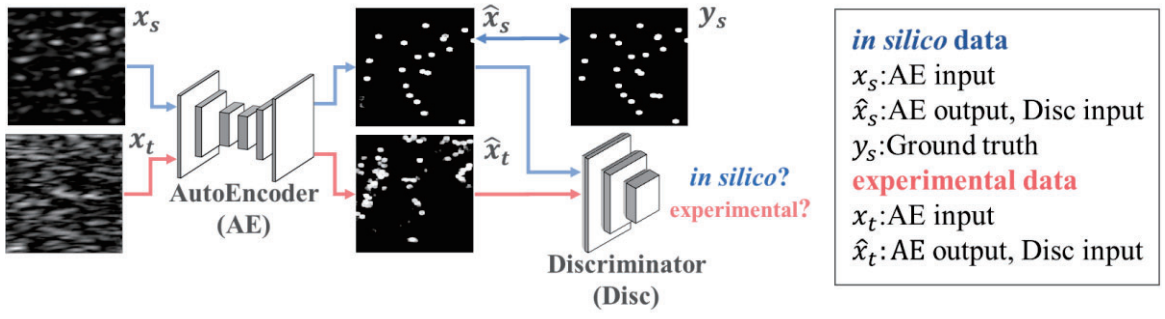

Fig. 1 Overview of the proposed learning method.

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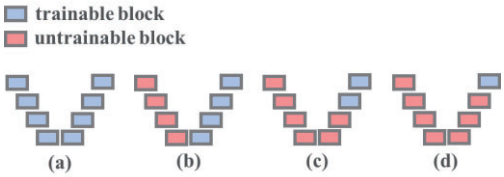

Fig. 2 Four fine-tuning methods.

The loss function in auto encoder was updated with deep learning parameters to increase the discriminator loss. On the other hand, the discriminator updated the parameters of the deep learning model so that the outputs of the segmentation result by the auto encoder could be accurately discriminated whether they were in silico or experimental data.

The adversarial learning strategy was introduced in the proposed method to suppress the misclassification of measured data while maintaining the segmentation accuracy of in silico data. In addition to the adversarial learning strategy, a fine-tuning method was performed using weights learned in advance using only in silico data as initial values. We compared the training strategy using four fine-tuning methods, i.e., proposed methods (a)-(d) shown in **Fig. 2**.

4. Results

Fig. 3 shows the results of the non-speckle detection area ratio at each number density in in silico and experimental data. The blue dashed line of in Fig. 3 (in silico) was evaluated by the conventional method. Other lines represent the experimental data evaluated by the conventional and proposed methods [(a)-(d)]. The detection ratio of in silico data was similar to that of experimental data using the proposed methods [(a)-(d)] compared to the conventional method. Furthermore, the fluctuation of the detection ratio in the proposed methods was more suppressed than the conventional method. **Table I** shows the result of the evaluation of each deep learning method. In the proposed method, the intersection over union (IoU) score of in silico data decreased by about 20%, but the error of the detection rate between in silico and experimental data was reduced against the conventional method. Since the results in the proposed methods [(a)-(d)] were comparable, it was considered that the minimum fine-tuning such as the proposed method [(d)] was enough to construct the model for this classification.

5. Conclusion

In this study, the adversarial learning method including experimental data (unknown ground truth) was investigated in the in silico-based model for segmentation of non-speckle components in blood echoes. As a result, the excessive detection of non-speckle components in the experimental data could be suppressed by the proposed strategy, and it could be adapted with the minimum fine-tuning. In future works, we will evaluate in vivo blood data.

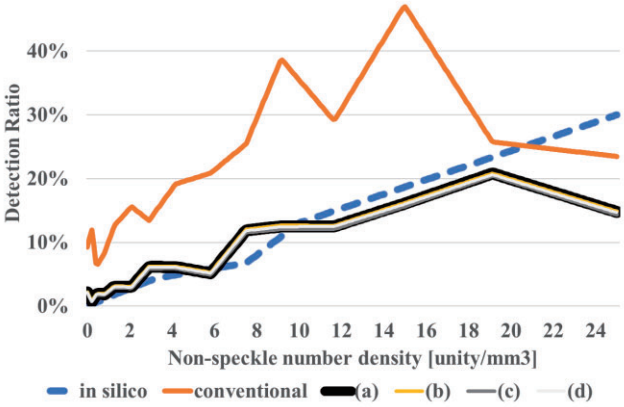

Fig. 3 Results of the non-speckle detection ratio in each number density.

Table. I Evaluation result in each deep learning method. IoU score was calculated from in silico dat a, and mean absolute error of detection ratio was computed between in silico and experimental data.

	IoU (in silico)	Mean Abs Error (detection ratio)
conventional	0.793	0.112
(a)	0.596	0.036
(b)	0.600	0.036
(c)	0.595	0.038
(d)	0.596	0.037

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References

1) M. Omura, K. Yagi, H. Hasegawa et al, J. Med. Ultrason. 50, 2023, p. 131-141.
2) Y. Mori, M. Mozumi, H. Hasegawa et al, Proc. 2022 Autmn Meet, Acoustical Society of Japan, 2022, 3-7Q-4 [in Japanese].
3) J.A. Jensen and N.B. Svendsen, 1992 IEEE Trans. Ultrason. Ferroelectr. Freq. Cont. 39, 1992, p. 262-267.
4) J.A. Jensen, Med. Biol. Eng. Comput. 34, 1996, p. 351-353.
5) O. Ronneberger, P. Fischer, T. Brox et al, MICCAI, Springer, 2015, p. 234–241.
6) I. Goodfellow, J. Pouget-Abadie, Y. Bengio et al, Proc. 2014 NIPS27, 2014.