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Deep learning for ultrasound echo speckle reduction and superresolution

深層学習による超音波エコー画像のスペックル低減と超解像

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1. Introduction

In our recent paper[1], for achieving high accuracy deep learning (DL) segmentation on an ultrasound (US) echo image, we propose to perform (i) speckle reduction and (ii) superresolution as preprocessing. For the speckle reduction, the Auto-Encorder (AE) model is effectively used, whereas for the superresolution, the well-known Super-Resolution Convolutional Neural Network (SRCNN), Fast SRCNN (FSRCNN) and Efficient sub-pixel CNN (ESPCN) are used, respectively. Since the superresolution results were not so effective for echo images, we have been searching for an effective DL model. Tentatively, we find the Deep Denoising Super Resolution CNN (DDSRCNN) and the Temporal Coherence Generative Adversarial Network (TecoGAN) and report the higher performances than others in another accompanying paper[2]. In this report, the combination performances of (i) AE and (ii) DDSRCNN and TecoGAN are evaluated for *in vivo* breast[3] and carotid[4] echo images.

2. Methods

The DDSRCNN can perform noise reduction as well as superresolution. The TecoGAN was first applied to video superresolution, which can substantially increase a spatial resolution while preserving the continuity of successive frames. Our research uses a convolutional autoencoder (CAE) for the speckle reduction. The sequence of approach I is that step i is performed first and then step ii is performed next. In step i, the CAE is used to reduce the speckles; and in step ii, super-resolution is performed using the DDSRCNN or the TecoGAN.

The distributed echo data[3] of human *in vivo* breast cancers and carotid arteries[4] were used, of which original pixel sizes and number of bits were 256 × 256 pixels and 8 bits, respectively. For the breasts, a US frequency ranged from 1 to 5 MHz; and for the carotids, two US frequencies (10 and 14 MHz) were used.

The breast original (GT) data were reduced into learning low resolution (LR) data with 85 × 85 pixels and 8 bits; and the carotid original data were made into learning LR data with the same pixel sizes through interpolating thinned 75 × 75 pixel ones. Additionally, the original breast and carotid data were also used as learning data.

For the LR data, all the learning parameters were set as follows for breasts and carotids: the number of learning data = 327 and 100; the epoch number = 300 and 100; and for the CAE and superresolutions, the learning rate = 0.0001 and 0.001; the batch size = 2 and 4. In addition, for the GT data as well as the LR data, the refined parameters were used as follows: the epoch number = 400; the leaning rate 0.0004.

3. Results

Figs. 1 and **2** respectively show for the breasts and carotids the obtained images with PSNRs defined in ref. 1 for evaluating the speckle reduction: (a) LR with nonrefined parameters and (b) LR with refine parameters (GT with refined parameters omitted).

Regarding **Fig. 1a**, for comparison, the PSNRs were 31.146 (approach I) and 31.214 (II) with ESPCN (images omitted). The CAE yields a high performance about the speckle reduction for a high spatial resolution image. As the reason described in ref. 1, since the superresolution should be performed on a high spatial resolution, the approach II was superior to approach I. For the data, TecoGAN also yielded similar results, i.e., 31.446 versus 31.143. However, for the DDSRCNN, vice versa. The DDSRCNN outputted high spatial resolutions with respect to low spatial resolution input data or an AE result. Thus, the order of a higher performance about superresolution is DDSRCNN > TecoGAN > ESPCN.

The results of **Fig. 1b** had higher resolutions than those of **Fig. 1a** by using the refined parameters for the same low spatial resolution input data. Approach I using DDSRCNN or TecoGAN

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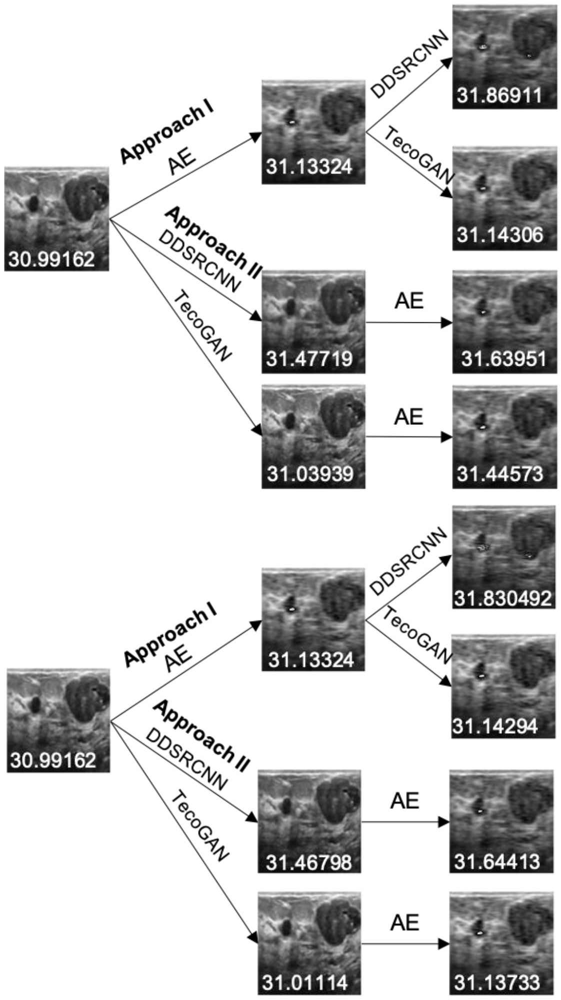


(a)

(b)

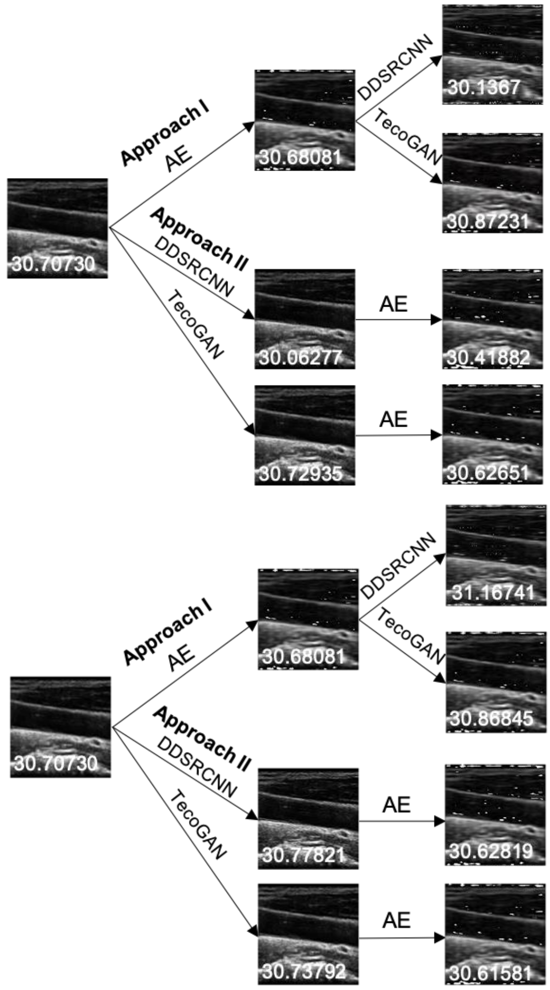
Fig. 1 Brest results obtained using LR data with (a) nonrefined and (b) refined parameters.

yielded larger PSNRs than Approach II, although the PSNRs had complex relations with respect to the resultant spatial resolutions. Using the same refined parameters for the GT data also yielded results similarly to **Fig. 1a** since the input GT data had a higher spatial resolution than that of **Fig. 1b**.

Next, **Fig. 2** shows for the carotid artery that Approach I yielded higher PSNRs than Approach II except for **Fig. 2a** using DDSRCNN. However, DDSRCNN increased spatial resolutions substantially. **Fig. 2b** using the refined parameters yielded much higher spatial resolutions than **Fig. 2a**, particularly with DDSRCNN. Maybe, the carotid data had lower spatial resolutions than the breast data. However, the input GT data did increase the spatial resolutions less than **Fig. 2b** since the GT data had a higher spatial resolution than that of **Fig. 2b**.

4. Conclusions

The DDSRCNN yielded high spatial resolutions, which led to substantial reduction of



(a)

(b)

Fig. 2 Carotid results. See caption of Fig. 1.

speckles. For the DDSRCNN and TecoGAN, the effects of a signal spatial resolution of input data will also be examined in detail in addition to signal-to-noise ratio and spatial sampling intervals (bandwidths), for instance, thorough simulations. We are also searching for the more effective speckle reduction model and segmentation model as well. Next, we'll report the segmentation results with DDSRCNN and TecoGAN.

References

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