2Pa5-5

Superreolution using TecoGAN and DDSRCNN for ultrasound echo image

TecoGan と DDSRCNN を用いた超音波エコー画像の超解像

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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 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 are not so effective for echo images, we are searching for an effective DL model. In this report, we evaluate performances of the Deep Denoising Super Resolution CNN (DDSRCNN)[2] and the Temporal Coherence Generative Adversarial Network (TecoGAN)[3] for human *in vivo* carotid[4] and breast[5] echo images.

2. Methods

2.1 DDSRCNN and TecoGAN

The DDSRCNN[2] can perform noise reduction as well as superresolution. By learning convolution and deconvolution layers' parameters to restore from a low-resolution noisy image toward the original image, removing noise and increasing spatial resolution can be achieved. TecoGAN[3] was first applied to video superresolution, which can substantially increase a spatial resolution while preserving the continuity of successive frames.

2.2 Human *in vivo* carotid and breast experiments

The distributed echo data[4] of human *in vivo* carotid arteries and breast cancers[5] were used, of which original pixel sizes and number of bits were 256 × 256 pixels and 24 bits. For the carotids, different linear-array-type transducers with two US frequencies (10 and 14 MHz) were used; and for the breasts, a US frequency ranged from 1 to 5 MHz. The original carotid data were used as a learning ground truth (GT) data, which were made into learning low resolution (LR1) data with the same pixel sizes and the same bits by interpolating thinned 75 × 75 pixel's data; and are subsequently made into LR2 data with small 8 bits. Similarly, the original breast (GT) data were also used as learning data, which were reduced into LR3 data with 85 × 85 pixels and 8 bits; and are subsequently made into LR4 data with 256 × 256 pixels by interpolation.

For the LR1 (carotids) and LR3 (breasts) data, learning parameters were set as follows: the number of learning data = 327 and 100, the epoch number = 300 and 100, respectively, and the learning rate = 0.001; and for ESPCN and others the batch size = 8 and 4, respectively. For the both GTs, LR2 and LR4 data, used were the refined parameters with the epoch number = 400 and the leaning rate = 0.0004.

3. Results

Figs. 1 and **2** show for the carotids and breasts the obtained superresolution images, respectively: **1a** and **2a** from the LR1 and LR3 with nonrefined parameters; **1b** and **2b** from the LR2 and LR4 with refined parameters; images from the GTs with refined parameters are omitted. All the results include ESPCN results. Moreover, the PSNR defined in ref. 1 is also depicted as a reference for evaluating speckle reduction.

For the carotids, **Fig. 1a** shows that the results of DDSRCNN have higher spatial resolutions than those of TecoGAN and the previous ESPCN visually, specifically, DDSRCNN > TecoGAN > ESPCN. However, the result of TecoGAN is rather similar to ESPCN including all other cases below. Interestingly, all the superresolution results also have higher contrasts than the input LR image. Next, the lower bit LR input of **Fig. 1b** has a coarser gradation than that of **Fig. 1a**; maybe leading to much higher spatial resolutions and contrasts, particularly the DDSRCNN. However, the omitted image of GT data, which is not so much different from the LR image in **Fig. 1a**, only the ESPCN increases a spatial resolution substantially. Actually, in ref. 1, the performance of ESPCN is remarkable for an input of a high spatial resolution image. Moreover, as confirmed, a spatial resolution higher,

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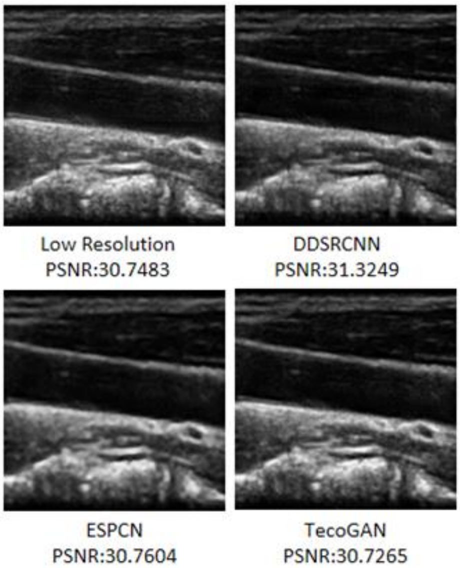
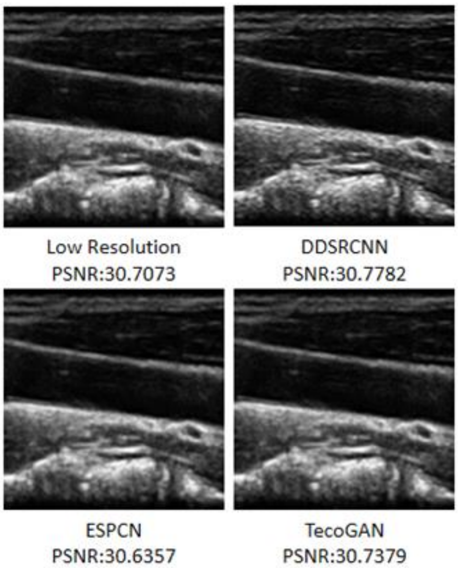
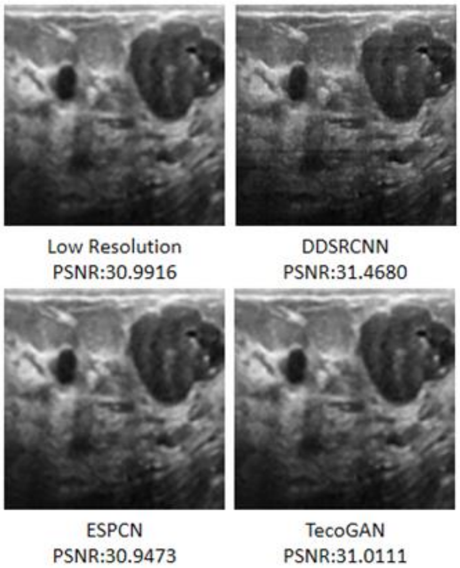


(a)

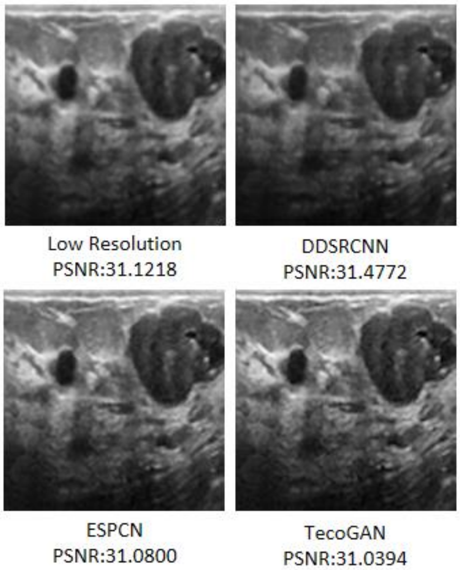


(b)

Fig. 1 Carotid results: (a) LR1 and (b) LR2.



(a)



(b)

Fig. 2 Breast results: (a) LR3 and (b) LR4.

a PSNR can become larger or smaller.

Next for the breasts, **Fig. 2a** shows that for the directly bit- and pixel-decreased input data from the GT data the order of performance is DDSRCNN > TecoGAN and ESPCN; **Fig. 2b** shows that for the input data spatially interpolated for the bit- and pixel-decreased data the order of performance is inverted, i.e., TecoGAN and ESPCN > DDSRCNN; and the omitted images from the GT input data show that the performance of DDSRCNN is slightly superior to others.

4. Conclusions

Being different from ESPCN, the performance of DDSRCNN is higher for more degraded input data. Moreover, the behavior of TecoGAN is similar to that of ESPCN[1]. In an accompanying paper[6], the effectiveness of the superresolution models for speckle reduction is evaluated with the AE.

References

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