Ultrasound Echo Speckle Reduction with Superresolution Using DDSRCNN and TecoGAN

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Abstract—In our accompanying paper [1], for achieving high accuracy deep learning (DL) segmentation on an ultrasound echo image, we propose to perform (i) speckle reduction and (ii) superresolution as preprocessing. For the speckle reduction, the Auto-Encoder (AE) model is effectively used, whereas for the superresolution, other effective DL models are found in another accompanying paper [2], i.e., the Deep Denoising Super Resolution CNN (DDSRCNN) and the Temporal Coherence Generative Adversarial Network (TecoGAN). In this report, the combination performances of (i) AE and (ii) DDSRCNN and TecoGAN are evaluated for in vivo breast echo images.

Clinical Relevance—Method effectiveness is confirmed for in vivo data.

I. INTRODUCTION

In our accompanying paper [1], for achieving high accuracy deep learning (DL) segmentation on an ultrasound echo image, we propose to perform (Step A) speckle reduction and (Step B) superresolution as preprocessing. For the speckle reduction, the Convolutional Auto-Encoder (CAE) 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 about (Step A) CAE and (Step B) DDSRCNN or TecoGAN are evaluated for in vivo breast echo images [3].

II. METHODS

The DDSRCNN can perform noise reduction as well as superresolution. The TecoGAN was first applied to video superresolution, which substantially increased the spatial resolution while preserving the continuity of successive frames. In our Approach I, Step A is performed first and Step B next; and in our Approach II, vice versa. The distributed echo data [3] of human in vivo breast cancers were used, of which average pixel sizes were 500 × 500 pixels. An ultrasound frequency ranged from 1 to 5 MHz. All parameters for DLs were set as follows: the number of learning data = 327; the epoch number = 300, the batch sizes = 2 (CAE), 8 (ESPCN) and 4 (others), and the learning rate = 0.0001. The original data were down-sampled to 256 × 256 pixels as Ground-truth (GT) data; and same pixel-size low-resolution (LR) data were made by interpolating thinned 85 × 85 pixel data.

III. RESULTS

Figure 1 shows the obtained images with PSNRs defined in ref. 1. As the reason described in ref. 1, Approach II was superior to Approach I for ESPCN (31.21 > 31.14, images omitted) and similarly to for TecoGAN (31.45 > 31.14). The CAE and superresolutions yield high performances for a high spatial resolution image. However, since DDSRCNN outputted high spatial resolutions even with respect to the low spatial resolution input data (a CAE result) and further reduced speckles, vice versa (31.87 > 31.64). Interestingly, the performance of speckle reduction was higher with DDSRCNN than with CAE (31.48 > 31.13). Then, CAE increased PSNR slightly up to 31.64. The order of a higher performance was DDSRCNN > TecoGAN > ESPCN.

IV. CONCLUSION

Next, we’ll report the segmentation and detection results with U-net and YOLO, etc. We are also searching for the more effective models.

REFERENCES