RF Data Restoration Using Convolutional Neural Networks for Data Rate Reduction in High-Frame-Rate Ultrasound Imaging

Di Xiao[1], Billy Y. S. Yiu[1], Adrian J. Y. Chee[1], Alfred C. H. Yu[1], [1]Schlegel Research Institute for Aging, University of Waterloo, Waterloo, Canada

Background, Motivation and Objective

Broad-view imaging has seen increasing use in recent years as an enabler of high-frame-rate ultrasound (HiFRUS); however, the raw data transfer rate associated with this paradigm (over 10GB/s of data acquired for over 1000 frames per second) remains to be a critical bottleneck for live imaging. While using fewer channels naturally reduces the data rate, this strategy comes with the expense of image quality degradation (e.g. grating lobe artifacts). Nonetheless, RF data from the remaining channels should contain features that can be utilized to restore signals of the omitted channels. Such data recovery could be achieved by deep learning to infer the missing channels. In this work, we propose a data reduction strategy that does not compromise image quality; it involves sparse sampling of the received aperture and reconstructing the missing samples using convolutional neural network (CNN).

Statement of Contribution/Methods

A CNN-based encoder-decoder was developed with four convolutional layers for encoding and four deconvolutional layers for decoding. Using a SonixTouch scanner (L14-5 array), over 2000 instances of *in vivo* human carotid unsteered plane wave data were collected to train the model (i.e. RF data feature extraction), with each instance consisting of 128 channels sampled at 20MHz. The interleaved channels were split, with odd-numbered channels used as inputs to the neural network and even-numbered used as training references. The network was then trained using the Adam optimizer on the Python Tensorflow module. To evaluate the performance of our approach, the trained network was used to reconstruct missing data acquired from a point target phantom; an image was subsequently beamformed and its image quality was used as performance indicator.

Results/Discussion

Image beamformed from CNN-reconstructed data (Fig. a) was comparable to the one generated from 128-channel data (Fig. b). Also, the grating lobe artifacts present in the images generated from linear-interpolated and sparse 64-channel data (Fig. c-d) was not observed in Fig. a. Specifically, at the depth where the lateral point target group is located, the grating lobe level of the CNN-reconstructed data was 10-15 dB lower than that for linear-interpolated and sparse 64-channel data. Overall, our proposed method shows potential in reducing the data rate for HiFRUS with limited image quality reduction.