Reconstruction Acceleration for Compressed Sensing Based Synthetic Transmit Aperture (CS-STA) with Deep Neural Network (DNN)

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Background, Motivation and Objective

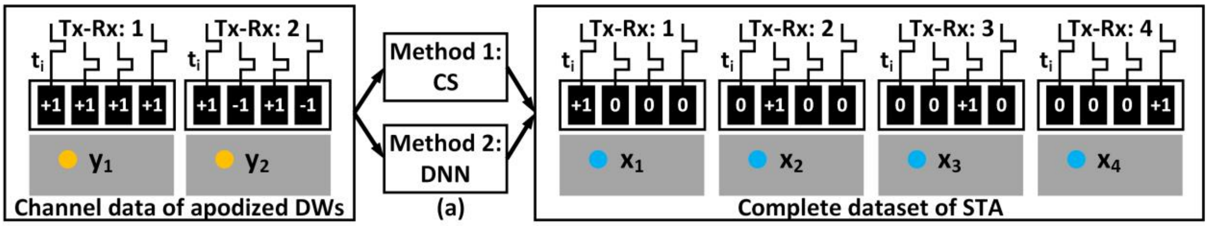
Diverging wave (DW) can realize high frame rate echocardiography at the expense of lower image quality. Alternatively, synthetic transmit aperture (STA) has better performance on image quality due to dynamic transmit focusing. However, STA has to compromise frame rate because of its single-element transmit scheme. Compressed sensing based STA (CS-STA) can decompose the contributions of every transmit element from the channel data of (partial) Hadamard-encoded DWs by CS method, in order to achieves high frame rate and image quality simultaneously (Liu and Luo, TUFFC 2018). A limitation of CS-STA is the long computational time in CS reconstruction. The aim of this work is to replace CS reconstruction with a deep neural network (DNN), in order to speed up this process under the premise of reconstruction accuracy.

Statement of Contribution/Methods

An illustration of CS-STA is shown in Fig (a). The conventional way of recover STA dataset (i.e., **x**) from the channel data of partial Hadamard apodized DWs (i.e., **y**) is iterative algorithm based CS reconstruction [Fig (b)]. The DNN-based method is illustrated in Fig (c). The DNN consists of an input layer with nodes equal to the number of DWs (i.e., 8, 16, or 32), an output layer with nodes equal to the number of elements (i.e., 64), two hidden layers with 512 nodes respectively. The ReLU is taken as the activation function, while the RMSE as the loss function. The training labels are the STA dataset of a standard phantom including wire, hyperechoic, and hypoechoic targets, acquired by a 64-element P4-2v phased array controlled by a Verasonics Vantage 256 system. The training data, i.e., the channel data of apodized DWs, are synthesized by the delayed and weighted summation of the training labels, according to Fig (a). *In-vivo* experiments of a healthy volunteer are conducted to validate the performance of this DNN.

Results/Discussion

The *in-vivo* echocardiography images of STA, CS and DNN-based methods with 32 transmits are shown in Fig (d). The normalized RMSE between the reconstructed dataset and STA dataset are listed in Table I, showing only slight difference between the DNN and CS methods. Moreover, in Table II, the computational time of the DNN method is around 1,000 times shorter than that of the CS method. In conclusion, the DNN method can realize CS-STA effectively and provide high quality echocardiography images with much less time consumption.



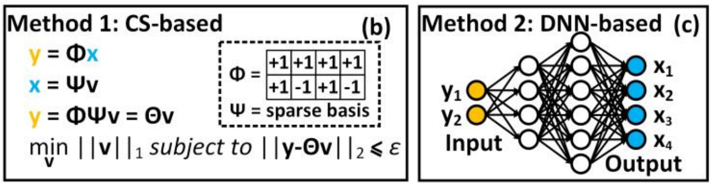


Table I. NRMSE (%) of reconstruction

No. Tx	CS vs. STA	DNN vs. STA	DNN vs. CS
8	2.88	2.61	0.56
16	2.53	2.48	0.43
32	2.36	2.26	0.35

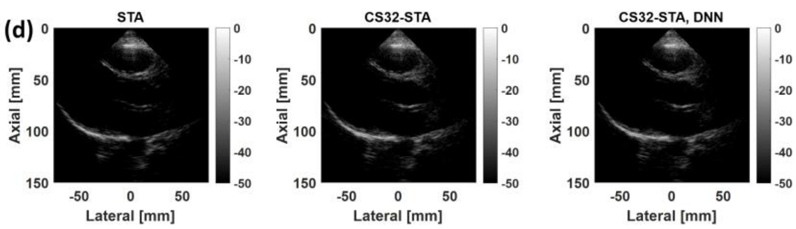


Table II. Time (s) of reconstruction

No. Tx	CS	DNN	Ratio
8	1735.84	1.35	1285.81
16	1897.24	1.58	1200.78
32	1647.70	1.86	885.86