Image Quality-Based Regularization for Deep Network Ultrasound Beamforming

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***Abstract*—Deep neural networks (DNNs) have previously been used to perform adaptive beamforming and improve image quality compared to conventional delay-and-sum (DAS). Although effective, low training validation loss is often not correlated to improved image quality, making model selection difficult. This discrepancy is due to these DNNs being optimized to perform an intermediate beamforming step instead of being optimized to enhance image quality on fully reconstructed images. Therefore, selecting model hyperparameters that produce optimal image quality has needed to be random and exhaustive. To address this problem, we propose a beamforming-relevant, end-to-end training scheme by using contrast-to-noise ratio (CNR) as a form of regularization. We compare a CNR-regularized DNN to a conventional DNN as well as DAS. When tested on simulated anechoic cysts, CNR-regularization resulted in 46% and 33% increases in CNR compared to the conventional DNN and DAS, respectively. When tested on *in vivo* data, CNR-regularization resulted in 68% and 25% increases in CNR compared to conventional DNN and DAS, respectively.**

***Index Terms*—CNR regularization, beamforming, ultrasound, deep learning**

I. Introduction

Several deep learning schemes have been proposed to perform adaptive beamforming more efficiently [1]–[7]. Among these approaches is a model-based deep neural network (DNN) beamformer that we developed previously [1]. Our implementation used a standard loss computed between regressed output and ground truth aperture domain signals for a single spatial location. Although effective at suppressing off-axis scattering, because these DNNs operate on aperture domain signals, image quality on fully reconstructed data is not always correlated to network performance.

This discrepancy makes model selection difficult. We previously demonstrated that image quality-related aperture domain coherence metrics can be incorporated into the loss function [8]. However, because this approach still operates on aperture domains signals, a discrepancy between network performance and the image quality metrics that we use for network evaluation can still persist.

To address this problem, we propose a contrast-to-noise ratio (CNR)-based regularization to improve correlation between network performance during training and at test time. This training scheme can be classified as end-to-end because our final metric, i.e., CNR, is included in our loss function [9]. Using CNR-regularization, we seek to demonstrate that image quality can be improved while maintaining network loss performance.

II. Methods

A. Data

Our networks are fully connected and operate on time delayed aperture domain signals to perform a regression-based beamforming for each received spatial location. A Hilbert transform was applied to all received channel data prior to network processing to generate real and imaginary components. Real and imaginary signals were concatenated. Training examples were generated from simulated anechoic cyst data. Test examples were generated from simulated anechoic cyst data as well as *in vivo* liver data.

Field II [10] was used to simulate channel data of 45 5mm diameter anechoic cyst realizations focused at 70mm using a 5.208MHz center frequency. Of the 45 realizations, 24 were used for training and 21 were used for testing. Simulated training data were split into accept and reject regions depending on whether the aperture signals originated from a location outside or inside of the cyst, respectively. Of the 24 training realizations, 4 were used for validation to determine stopping criteria. A total of 131,904 aperture domain examples were used for training. To compute CNR during training, each mini batch consisted of examples from a single cyst realization.

A Verasonics Vantage Ultrasound System (Verasonics, Inc., Kirkland, WA) and ATL L7-4 (38mm) linear array transducer were used to acquire test channel data of 15 different fields of view of a 36 year old healthy male liver. Consent was given in accordance with the local institutional review board. Acquisition parameters matched those used for simulations.

B. CNR Regularization

Aperture domain examples were normalized prior to being passed through a DNN. The stacked real and imaginary output data from the network were then unnormalized, combined into analytic data, and summed across the aperture domain. The magnitude was taken to compute the envelope of each signal. CNR was then computed on the envelope data for which specified background and lesion examples were used to compute CNR as follows,

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$$CNR = 20log_{10}\frac{|\mu_{background} - \mu_{lesion}|}{\sqrt{\sigma^2_{background} + \sigma^2_{lesion}}} \quad (1)$$

where μ and σ are the mean and standard deviation of the uncompressed envelope. As described in the following subsection, training data were made from simulated anechoic cysts which have a theoretical inherent CNR of 5.6dB. Therefore, a CNR loss was computed as follows,

$$L_{CNR} = \lambda||CNR_{out} - 5.6||_l \quad (2)$$

where λ is a scaling term, CNR_{out} is the estimated CNR on the output data from the model, and l represents the type of loss function used. A fixed λ value of 0.005 and a smooth L1 loss function was used in this work. The above CNR loss function is then added to the standard data fidelity loss function, L_F, computed on the regressed output signals compared to the target signals as follows,

$$L = L_F + L_{CNR} \quad (3)$$

C. Evaluation

The proposed CNR-DNN approach was compared to conventional DAS as well as a DNN trained without CNR regularization but with otherwise similar model parameters. CNR and contrast ratio (CR) were used to evaluate beamformer performance. CNR was computed as in Eq. (1), and CR was computed as follows,

$$CR = -20\log_{10}\frac{\mu_{lesion}}{\mu_{background}} \quad (4)$$

where μ is the mean of the uncompressed envelope. Images were made for qualitative comparison by log compressing the envelope data and scaling to a 60dB dynamic range.

III. Results

Both CNR-regularized and conventional DNN approaches converged to relatively low validation loss, as shown in the top of Fig. 1. However, substantially higher CNR is achieved on simulated training and validation data when using CNR regularization compared to conventional DNN beamforming, as shown in the bottom of Fig. 1. The CNR-regularized DNN converges to CNR values that are closer to 5.6dB compared to the conventional DNN approach.

CNR-regularization improves image quality compared to conventional DNN and DAS when tested on simulated anechoic cysts and *in vivo* liver data. As shown in Fig. 2, the conventional DNN approach suppresses signal within the simulated and *in vivo* cysts, but it also results in more speckle dropout, resulting in CNR values less than those achieved with DAS. In contrast, the CNR-based DNN preserves CR improvements compared to DAS while also improving CNR. Quantitatively, the CNR-based DNN resulted in the highest CNR on average in both simulations and *in vivo* data as shown in Tables I and II.

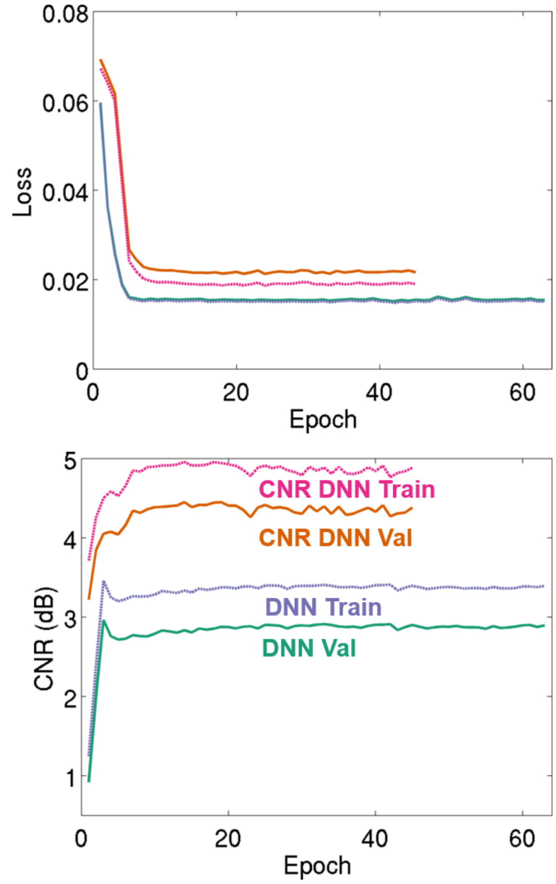

Fig. 1. Training and validation loss curves are shown on top for DNN (purple and teal, respectively) and CNR-DNN (pink and orange, respectively). Average CNR computed on training subset ($N = 4$) and validation data ($N = 4$) is shown in the bottom plot for DNN (purple and teal, respectively) and CNR-DNN (pink and orange, respectively).

TABLE I
AVERAGE CNR AND CR ($\pm$ STANDARD DEVIATION) ACROSS THE 21 SIMULATED TEST EXAMPLES

Method	CNR (dB)	CR (dB)
DAS	5.06 ($\pm$0.21)	28.0 ($\pm$0.81)
DNN	4.62 ($\pm$0.22)	34.6 ($\pm$1.07)
CNR-DNN	6.75 ($\pm$0.23)	31.5 ($\pm$1.08)

IV. Conclusion

DNN beamformers have been shown to improve image quality compared to conventional DAS. However, low training validation loss is often not correlated to improved image quality because these DNNs operate on aperture domain data. To address this problem, we propose a CNR-regularization scheme that optimizes for CNR on fully reconstructed data during training. We compare our approach to a conventional DNN as well as to DAS. We show that CNR-regularized DNNs achieve low validation loss while also improving image quality on simulated anechoic cyst and *in vivo* test data.

TABLE II
AVERAGE CNR AND CR (± STANDARD DEVIATION) ACROSS THE 15 *in vivo* TEST EXAMPLES

Method	CNR (dB)	CR (dB)
DAS	1.78 (±1.13)	14.3 (±5.29)
DNN	1.33 (±1.20)	17.8 (±5.96)
CNR-DNN	2.23 (±1.17)	15.6 (±5.51)

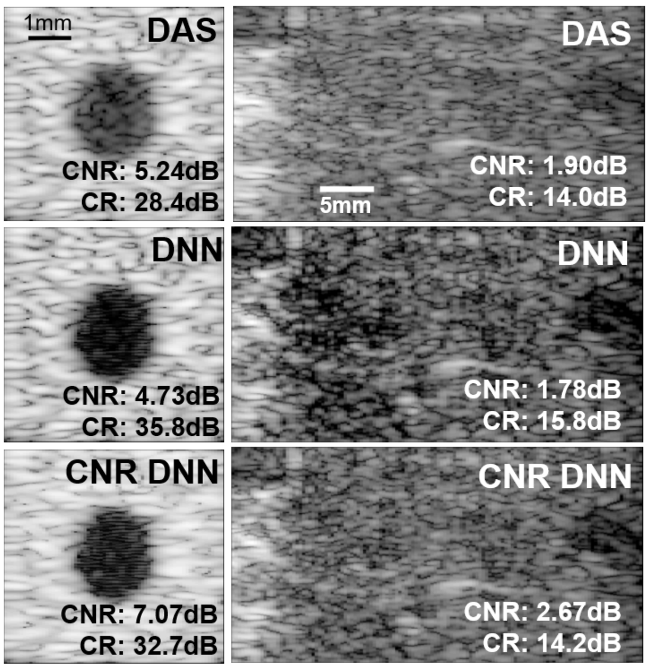

Fig. 2. Example simulated anechoic cyst (left) and *in vivo* (right) B-mode images are shown for DAS, DNN, and CNR-regularized DNN. All images are scaled to individual maximums and a 60dB dynamic range.

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