Adaptive and Compressive Beamforming using Deep Learning for Medical Ultrasound

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Abstract—In ultrasound (US) imaging, various types of adaptive beamforming techniques have been investigated to improve the resolution and contrast to noise ratio of the delay and sum (DAS) beamformers. Unfortunately, the performance of these adaptive beamforming approaches degrade when the underlying model is not sufficiently accurate and the number of channels decreases. To address this problem, here we propose a deep learning-based end-to-end beamformer to generate significantly improved images over widely varying measurement conditions and channel subsampling patterns. In particular, our deep neural network is designed to directly process full or sub-sampled radio-frequency (RF) data acquired at various subsampling rates and detector configurations so that it can generate high quality ultrasound images using a single beamformer. The origin of such adaptivity is also theoretically analyzed. Experimental results using B-mode focused ultrasound confirm the efficacy of the proposed methods.

Index Terms—Ultrasound imaging, B-mode, beamforming, adaptive beamformer, Capon beamformer

I. INTRODUCTION

Excellent temporal resolution with reasonable image quality makes the ultrasound (US) modality a first choice for a variety of clinical applications. Moreover, due to its minimal invasive-ness, US is an indispensable tool for some clinical applications such as cardiac, fetal imaging, etc.

In US, an image reconstruction is usually done by back-propagating the preprocessed measurement data and adding all the contributions. For example, in focused B-mode US imaging, the return echoes from individual scan line are recorded by the receiver channels, after which a delay and sum (DAS) beamformer applies appropriate time-delays to the channel measurements and additively combines them for each depth to form images at each scan line.

Despite the simplicity, large number of receiver elements are often necessary in DAS beamformer to improve the image quality by reducing the side lobes. Moreover, to calculate accurate time delay, sufficiently large bandwidth transducers are required. Accordingly, to deal with various unfavorable acquisition conditions, various adaptive beamforming techniques have been developed over the several decades [1]–[9]. The main idea of adaptive beamforming is to change the receive aperture weights based on the received data statistics to improve the resolution and enhance the contrast. One of the most extensively studied adaptive beamforming techniques is Capon beamforming, also known as the minimum variance (MV) beamforming [2]–[4]. The aperture weight of Capon beamformer is derived by minimizing the side lobe while maintaining the gain in the look-ahead direction. Unfortunately, Capon beamforming is computational heavy for practical use due to the calculation of the covariance matrix and its inverse [5]. Moreover, the performance of Capon beamformer is dependent upon the accuracy of the covariance matrix estimate. To address these problems, many improved version of MV beamformers have been proposed [4]–[7]. Some of the notable examples includes the beamspace adaptive beamformer [6], multi-beam Capon based on multibeam covariance matrices [8], etc. In addition, a parametric form of iterative update covariance matrix calculation has been proposed instead of calculating the empirical covariance matrix [9].

Recently, inspired by the tremendous success of deep learning, many researchers have investigated deep learning approaches for various inverse problems [10]–[21]. In US literature, the works in [22], [23] were among the first to apply deep learning approaches to US image reconstruction. In particular, Allman et al. [22] proposed a machine learning method to identify and remove reflection artifacts in photo-acoustic channel data. Luchies and Byram [23] proposed a frequency domain deep learning method for suppressing off-axis scattering in ultrasound channel data. In [24], a deep neural network is designed to estimate the attenuation characteristics of sound in human body. In [25], [26], ultrasound image denoising method is proposed for the B-mode and single angle plane wave imaging. Rather than using deep neural network as a post processing method, the authors in [27]–[30] employed deep neural networks for the reconstruction of high-quality US images from limited number of received RF data. For example, the work in [28] uses deep neural network for coherent compound imaging from small number of plane wave illumination. In focused B-mode ultrasound imaging, [27] employs the deep neural network to interpolate the missing RF-channel data with multilinie aquisition for accelerated scanning. In [29], [30], the authors employ deep neural networks for the correction of blocking artifacts in multilinie acquisition and transmission scheme.

While these recent deep neural network approaches provide impressive reconstruction performance, the designed neural network cannot completely replace a DAS beamformer, since they are designed as pre- or post- processing steps for specific acquisition scenario and many of the works employ the standard DAS beamformer.

Therefore, one of the most important contributions of this paper is to completely replace the DAS and adaptive beamformers with a deep learning-based data-driven adaptive beamformer (DeepBF) so that a single DeepBF can generate
high quality images robustly for various detector channel configurations. Moreover, unlike the MV beamformer that can be used only for uniform array, our DeepBF is designed for various detectors and RF subsampling schemes, in spite of significantly reduced run-time computational complexity. In contrast to [27], where the deep learning approach was developed to interpolate missing RF data to be used as input to the standard beamformer, the proposed method is an end-to-end CNN-based beamforming pipeline, without requiring additional beamformer. Consequently, this approach is much simpler and can be easily incorporated to replace the standard beamforming pipeline. Despite the simplicity, our experiments show that direct reconstruction using the proposed DeepBF produces better results compare to [27].

The consistent performance improvement over DAS and MV beamformer using a single CNN may appear mysterious. Inspired by the recent theoretical extension [31] of deep convolutional framelets [32], another important contribution of this paper is, therefore, a detailed theoretical analysis to identify the origin of the adaptivity and performance improvement of DeepBF. Our theoretical analysis suggests that the deep learning-based beamformer is indeed the right direction for medical ultrasound.

After the initial work of this paper was available on Arxiv [33], a related work on deep learning based adaptive beamformer appeared [34]. In contrast to the proposed method, [34] is interested in estimating the adaptive beamformer weights using a deep neural network. Moreover, the results are only available for simple phantom data, the application of compressive beamforming was not considered, and the theoretical reason to unveil why the deep learning beamformer works was not provided. Therefore, our work is more general and provides a systematic understanding in designing deep learning based beamformer.

This paper is organized as follows. In Section II, a brief survey of the existing adaptive beamforming methods are provided, which is followed by the detailed explanation of the proposed deep beamformer in Section III. Section IV then describes the data set and experimental setup. Experimental results are provided in Section V, which is followed by Discussion and Conclusions in Section VI and Section VII.

II. RELATED WORKS

A. DAS beamforming

The standard delay and sum (DAS) beamformer for the $l$-th scan line at the depth sample $n$ can be expressed as

$$ z_l[n] = \frac{1}{J} \sum_{j=0}^{L-1} y_{l,j}[n], \quad l = 0, \ldots, L-1, $$

where $\top$ denotes the transpose, $J$ denotes the number of active receivers, $1$ denotes a length $J$ column-vector of ones, and $y_{l}[n]$ refers to the scan line dependent time reversed RF data defined by

$$ y_{l}[n] = [y_{l,0}[n] \; y_{l,1}[n] \; \cdots \; y_{l,J-1}[n]]^\top. $$

Here, $y_{l,j}[n] := x_{l,j}[n - \tau_j[n]]$, where $x_{l,j}[n]$ is the RF echo signal measured by the $j$-th active receiver element from the transmit event (TE) for the $l$-th scan line, and $\tau_j[n]$ is the dynamic focusing delay for the $j$-th active receiver elements to obtain the $l$-th scan line.

B. Adaptive beamforming

The DAS beamformer is designed to extract the low-frequency spatial content that corresponds to the energy within the main lobe; thus, it is difficult to control side lobe leakage. Reduced side lobe leakage can be achieved by replacing the uniform weights by tapered weights:

$$ z_l[n] = w_l[n]^\top y_l[n], $$

where $w_l[n] = [w_{l,0}[n] \; w_{l,1}[n] \; \cdots \; w_{l,J}[n]]^\top$. Specifically, in adaptive beamforming the objective is to find the $w_l$ that minimizes the variance of $z_l$, subject to the constraint that the gain in the desired beam direction equals unity. For example, the minimum variance (MV) estimation task can be formulated as [2–4]

$$ \begin{align*}
\text{minimize}_{w_l[n]} \quad & E[|z_l[n]|^2] \\
\text{subject to} \quad & 1^\top w_l[n] = 1,
\end{align*} $$

where $E[\cdot]$ is the expectation operator, and $R_l[n]$ is a spatial covariance matrix given by:

$$ R_l[n] = E[ y_l[n]^\top y_l[n] ]. $$

Then, $w_l[n]$ can be obtained by Lagrange multiplier method [35] and expressed as

$$ w_l[n] = \frac{R_l[n]^{-1}}{1^\top R_l[n]^{-1} 1}. $$

C. Deconvolution Ultrasound

One of the main limitations of the aforementioned beamforming method is that they are based on the ray approximation of the wave propagation, whereas the real sound propagations exhibits many wave phenomenon such as scattering, etc. Moreover, the precision of the time delay $\tau_j[n]$ calculation is determined by bandwidth of the transducers, which limits the accuracy of delayed signal $y_{l,j}[n] := x_{l,j}[n - \tau_j[n]]$. These modeling inaccuracy indeed affects the spatial resolution and the contrast of standard US images.

In order to overcome these issues, many researchers have explored the deconvolution of US images [36], [37]. Specifically, the deconvolution US tries to find the deconvolution kernel $h_l[n]$ such that the deconvoluted signal $v_l[n]$ given by

$$ v_l[n] = h_l[n] * z_l[n] $$

$$ = \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} h_{l-p}[q] z_p[n - q] $$

produces high resolution images, where $h_l[n]$ refers to the deconvolution filters. Usually, the deconvolution is performed under regularization, so that the corresponding filter becomes spatially varying.
respectively, given by the discrete form Hilbert transform. Here, \( b_i \) where \( \tilde{b}_i \) represents the input RF data vector across multiple depths. The aim of the US reconstruction is then to find the matrices \( B \) and \( \tilde{B} \) so that the processed image has a high resolution with good contrast and better signal-to-noise ratio.

III. MAIN CONTRIBUTION

A. Combinatorial representation learning using CNN

In practice, the estimation of \( T \) in (9) in terms of \( \tilde{B} \) and \( B \) is technical challenging. Specifically, the elements of \( B \) are beamformer weights that are dependent on each data \( u[n] \) and the depth \( n \). Moreover, the deconvolution filter matrix in \( B \) should be spatially varying and depends on \( n \) to make the best trade-off between the noise and resolution. Therefore, the exact calculation is usually computationally expensive, and only approximate forms are used, which limits the accuracy of the beamformer. A quick remedy to reduce the run-time computational complexity would be precalculating nonlinear mapping \( T \). Unfortunately, as stated before, the mapping \( T \) depends on the input, so it requires huge memory to store \( T \) for all inputs.

In this regard, a convolutional neural network (CNN) using ReLU nonlinearities provides an ingenious way of addressing this issue. Specifically, in our recent theoretical work [31], we have shown that an encoder-decoder CNN with ReLU nonlinearity generates large number of locally linear mappings. More specifically, the input space \( \mathcal{X} \) is partitioned into non-overlapping regions where input for each region shares the common linear representation. Then, the switching to the corresponding linear representation for each input can be done instantaneously based on the ReLU activation patterns.

![Fig. 1. Encoder-decoder CNN backbone.](image)

Specifically, consider an encoder-decoder CNN with skipped connection as shown in Fig. 1 where there exists skipped connection for every three convolution operations. At the \( l \)-th layer, \( m_l \) and \( q_l \) denote the dimension of the signal, and the number of filter channel, respectively. We consider symmetric configuration so that both encoder and decoder have the same number of layers, say \( \kappa \). Now, let the \( l \)-th layer signal, which is either input, features, or output, be denoted by

\[ Z^l := \begin{bmatrix} z_1^l & \cdots & z_{q_l}^l \end{bmatrix}, \quad z^l := \text{VEC}(Z^l). \]

Then, by following the derivation in [31], it is easy to show that the \( l \)-th encoder layer can be represented by

\[ z^l = \sigma(B^T z^{l-1}) \]
and values that are determined by the ReLU output in \( \Lambda \) where \( b \) represents the channel input. Similarly, we define the skipped branch signal \( I \) and \( \sigma \) represents a multi-channel convolution \( [31] \). Then, the \( l \)-th layer decoder filter to generate the \( i \)-th channel output from the contribution of the \( j \)-th channel input, and \( \otimes \) represents a multi-channel convolution \( [31] \). Then, the \( l \)-th decoder layer can be represented by

\[
\tilde{z}_l^{i-1} = \sigma(D^l \tilde{z}_l^i) \tag{15}
\]

where

\[
D^l = \begin{bmatrix}
I_{m_l} \otimes \psi_{i,l,1} & \cdots & I_{m_l} \otimes \psi_{i,q_l,1} \\
I_{m_l} \otimes \psi_{i,q_l+1,1} & \cdots & I_{m_l} \otimes \psi_{i,q_l+1,q_l} \\
\vdots & \ddots & \vdots \\
I_{m_l} \otimes \psi_{i,1,q_l} & \cdots & I_{m_l} \otimes \psi_{i,1,1}
\end{bmatrix} \tag{16}
\]

Then, by following the derivation in \( [31] \), it is straightforward to show that the output \( v^a \) of the encoder-decoder CNN with respect to input \( z \) can be represented by the following nonlinear frame-like representation:

\[
v^a = T_\Theta z = \sum_i \langle b_i(z), z \rangle b_i(z) \tag{18}
\]

where \( \Theta \) refers to all the convolution filter parameters, and \( b_i(z) \) and \( b_i(z) \) denote the \( i \)-th column of the following frame basis and its dual, respectively:

\[
B(z) = \begin{bmatrix}
E^1 \Lambda^1(z) E^2 \cdots \Lambda^{k-1}(z) E^k \\
\vdots \\
E^1 \Lambda^1(z) E^6, E^1 \Lambda^1(z) \cdots E^3
\end{bmatrix} \tag{19}
\]

\[
\hat{B}(z) = \begin{bmatrix}
D^1 \Lambda^1(z) D^2 \cdots \Lambda^{k-1}(z) D^k \\
\vdots \\
D^1 \Lambda^1(z) D^6, D^1 \Lambda^1(z) \cdots D^3
\end{bmatrix} \tag{20}
\]

where \( \Lambda^i(z) \) and \( \hat{\Lambda}^i(z) \) denote the diagonal matrix with 0 and 1 values that are determined by the ReLU output in the previous convolution steps. Note that there are skipped connections at every third convolution operations in Fig. 1 so that the last blocks in (19) and (20) are indexed accordingly.

The expression (18) reveals many important aspects of neural networks. First, the CNN representation in (18) has explicit dependency on the input \( z \) in \( [15] \), due to the ReLU output \( \Lambda^i(z) \) and \( \hat{\Lambda}^i(z) \). This makes the frame-like representation vary depending on the input signals. In fact, thanks to the combinatorial nature of ReLU, the number of distinct linear representation increases exponentially with the depth, and width \( [31] \). Moreover, the number of blocks in \( B(z) \) and \( \hat{B}(z) \) in (19) and (20) are determined by the number of skipped connections, so the skipped branch makes the frame-like representation more redundant, which again makes the neural network more expressive \( [31] \).

Note that the representation in (18) is strikingly similar to our adaptive beamformer representation in (9). This implies that the adaptive beamforming can be learned using an encoder-decoder CNN. For example, our DeepBF neural network training can be done to estimate the filters \( \Theta \):

\[
\min_{\Theta} \sum_{i=1}^N ||v^{a(i)} - T_\Theta z^{(i)}||_2^2, \tag{21}
\]

where \( \{z^{(i)}, v^{a(i)}\}_{i=1}^N \) denotes the training data set composed of RF data and the target IQ data at a specific depth, which are collected across all depth, subjects and subsampling patterns. Here, we can design our CNN with relatively small parameter sets to deal with extremely large number of distinct input RF data, since the number of associated linear representations increases exponentially with the network depth, width, and skipped connection. This expressivity and adaptivity are believed to be the main origin of the superior performance of deep neural networks, which is ideal for data-driven compressive and adaptive beamforming.

Fig. 2 illustrates the proposed DeepBF pipeline using the reflected sound waves in the medium measured by the transducer elements. As a preprocessing for DeepBF pipeline, each measured signal is time-delayed based on the traveled distance to perform beam-focusing. Then, our DeepBF generates IQ data directly from the time delayed RF data across three depth planes. Compared to the standard DAS beamformer, this corresponds to the replacement of the deconvolution,
beamforming and Hilbert transform parts with a deep neural network. Then, the signal envelope is generated by calculating the sum of squares of the in-phase and quadrature phase signals generated from the Hilbert transform. Finally, the log compression is applied to generate the B-mode images.

IV. METHOD

A. Dataset

For experimental verification, we used an E-CUBE 12R US system (Alpinion Co., Korea). For data acquisition, we used a linear array transducer (L3-12H), whose configuration is given in Table I. Specifically, using the linear probe with a center frequency of 8.5 MHz, we acquired RF data from the carotid area of 10 volunteers. The in vivo data consist of 40 temporal frames per subject, providing 400 sets of Rx-TE-Depth data cube. For all scans the axial depth was in the range of 20~80 mm, while lateral length was 40mm. In addition, we acquired 218 frames of RF data from the ATS-539 multipurpose tissue mimicking phantom using three different center frequencies. This dataset was only used for test purposes and no additional training of CNN was performed on it.

| TABLE I PROBE CONFIGURATION |
|-----------------------------|
| Parameter                  | Linear Probe |
| Probe Model No.             | L3-12H       |
| Carrier wave frequency      | 8.5 / 10 / 11.5 MHz |
| Sampling frequency          | 40 MHz       |
| No. of probe elements       | 192          |
| No. of Tx elements          | 128          |
| No. of TE events            | 96           |
| No. of Rx elements          | 64           |
| Elements pitch              | 0.2 mm       |
| Elements width              | 0.14 mm      |
| Elevating length            | 4.5 mm       |

B. Network specification

Fig. 1 illustrates the schematic diagram of our deep beamformer. One minor improvement is the channel augmentation at the skipped branch of the decoder rather than simple addition. The proposed CNN consists of 28 convolution layers (i.e. \( \kappa = 4 \)) composed of a contracting path with concatenation, batch normalization, and ReLUs except for the last convolution layer. The first 27 convolution layers use \( 3 \times 3 \) convolutional filters (i.e., the 2-D filter has a dimension of \( 3 \times 3 \)), and the last convolution layer uses a \( 3 \times 1 \) filter followed by an average pooling to contract the \( 64 \times 96 \times 3 \) data-cube from Rx-TE-Depth sub-space to \( 1 \times 96 \times 2 \) Depth-TE-IQ plane. The number of channel for each layer is \( q_l = 64 \) and the dimension of the signal is \( m_l = 64 \times 96 \) up to the last layer which shrinks it to \( 1 \times 96 \times 2 \) Depth-TE-IQ data.

C. RF data sampling scheme

The input and output data configurations are shown in Fig. 2. The time-delayed RF data cube is a three-dimensional data cube composed of total 1280 ~ 4608 depths of \( 64 \times 96 \) data in Rx-TE direction. We trained our neural network using multiple input/output pairs, where an input consists of \( 64 \times 96 \times 3 \) data-cube in the Rx-TE-Depth volume and the output is composed of 96 pairs of I/Q data in the Depth-TE plane. Each target IQ pair corresponds to two output channels, each representing real and imaginary parts. A set of 30,000 Rx-TE-Depth cubes of size \( 64 \times 96 \times 3 \) was randomly selected from four subjects datasets, which are divided into 25,000 datasets for training and 5,000 datasets for validation. The remaining dataset of 360 frames was used as a test dataset.

For our experiments, in addition to the full RF data with \( 64 \) RF-channels, we generated five sets of sub-sampled RF data at different down-sampling rates. More specifically, the subsampling cases included 32, 24, 16, 8 and 4 Rx-channels at variable down-sampling patterns across the depth. Since the active receivers at the center of the scan line get RF data from direct reflection, two channels that are in the center of active transmitting channels were always included to improve the performance, and the remaining channels were randomly selected from the total 64 active receiving channels.

D. Network training

As for the target IQ data, we use the IQ data from DAS beamforming results from the full RF data. One could use IQ data from an adaptive beamformer, but we chose the DAS data as target data, because 1) DAS beamformer is more robust than the adaptive beamformer results for various acquisition scenario, and 2) we are interested in showing that the neural network trained with DAS results can outperform the original DAS reconstruction results thanks to the synergistic combination from the various data and depths.

The network was implemented with MatConvNet [39] in the MATLAB 2015b environment. Specifically, for network training, the parameters were estimated by minimizing the \( l_2 \) norm loss function using a stochastic gradient descent with a regularization parameter of \( 10^{-4} \). The learning rate started from \( 10^{-4} \) and gradually decreased to \( 10^{-7} \) in 200 epochs. The weights were initialized using Gaussian random distribution with the Xavier method [40].

E. Comparison methods

For the evaluation purpose, we compared our proposed DeepBF method with standard DAS and MV beamformers.

In DAS, the beamforming step is a simple sum. Specifically, for DAS formulation in (1), \( J \) is varied from 64 to 4 depending on the sub-sampling ratios so that data from \( J \) active receivers is added to generate beamformed output. For the adaptive
beamforming case, $\mathbf{R}_c[n]$ must be estimated with a limited amount of data. A widely used method for the estimation of $\mathbf{R}_c[n]$ is spatial smoothing (or subaperture averaging) [41], in which the sample covariance matrix is calculated by averaging covariance matrices of $K$ consecutive channels in the $J$ receiving channels as follows:

$$\tilde{\mathbf{R}}_c[n] = \frac{1}{J-K+1} \mathbf{Y}_c[n] \mathbf{Y}_c^\top[n],$$

where

$$\mathbf{Y}_c[n] = \begin{bmatrix} y_{c,0}[n] & \cdots & y_{c,J-K}[n] \\ \vdots & \ddots & \vdots \\ y_{c,K-1}[n] & \cdots & y_{c,J-1}[n] \end{bmatrix},$$

which can be made invertible when $K \leq J/2$. Here in this paper we use $K = 16$. Then, the weight for the minimum variance beamformer is calculated via (5) using the covariance estimate (22), after which the final beamforming result (3) is obtained by averaging the contribution from the adaptive beamforming results from each subaperture array.

F. Performance metrics

To quantitatively show the advantages of the proposed deep learning method, we used the contrast-ratio (CR), contrast-to-noise ratio (CNR) [42], generalized CNR (GCNR) [43], peak-signal-to-noise ratio (PSNR), structure similarity (SSIM) [44] and the reconstruction time.

The contrast is measured for the background ($B$) and anechoic structure ($aS$) in the image, and quantified in terms of CR and CNR:

$$\text{CR}(B, aS) = |\mu_B - \mu_{aS}|$$

$$\text{CNR}(B, aS) = \frac{|\mu_B - \mu_{aS}|}{\sqrt{\sigma_B^2 + \sigma_{aS}^2}},$$

where $\mu_B$, $\mu_{aS}$, and $\sigma_B$, $\sigma_{aS}$ are the local means, and the standard deviations of the background ($B$) and anechoic structure ($aS$) [42]. Another improved measure for the contrast-to-noise-ratio called generalized-CNR (GCNR) was recently proposed [43]. The GCNR compare the overlap between the intensity distributions of two regions. The GCNR is defined as

$$\text{GCNR}(B, aS) = 1 - \int \min\{p_B(x), p_{aS}(x)\} dx,$$

where $x$ is the pixel intensity, and $p_B$ and $p_{aS}$ are the probability distributions of the background ($B$) and anechoic structure ($aS$), respectively. If both distribution are completely independent, then GCNR will be equals to one, whereas, if they completely overlap then GCNR will be zero [43]. The GCNR measure is difficult to tweak, so we believe that GCNR is an objective performance metric. For CNR and GCNR calculations, we generated separate ROI masks for each image.

The PSNR and SSIM index are calculated on reference ($v$) and Rx sub-sampled ($\tilde{v}$) images of common size $n_1 \times n_2$ as

$$\text{PSNR}(v, \tilde{v}) = 10 \log_{10} \left( \frac{n_1 n_2 R_{\text{max}}^2}{\|v - \tilde{v}\|_F^2} \right),$$

$$\text{SSIM}(v, \tilde{v}) = \frac{(2\mu_v\mu_{\tilde{v}} + c_1)(2\sigma_{v,\tilde{v}} + c_2)}{\mu_v^2 + \mu_{\tilde{v}}^2 + c_1(\sigma_v^2 + \sigma_{\tilde{v}}^2 + c_2)},$$

where $\| \cdot \|_F$ denotes the Frobenius norm and $R_{\text{max}} = 2^{(\#\text{bits per pixel})} - 1$ is the dynamic range of pixel values (in our experiments this is equal to 255), and

In this section we present extensive comparison results of our method with DAS and the minimum variance beamformer (MVBF) for various acquisition scenarios.

A. Full RF data cases

1) Reconstruction results on phantom dataset: In Fig. 4 we compared two phantom examples scanned using 8.5 MHz center frequency. In phantom test dataset, the proposed method achieve comparable or even better performance compared to DAS and MVBF methods. From the figures we found that the visual quality of DeepBF reconstruction, especially around anechoic regions, is comparable or better than that of MVBF method, which is better than DAS beamformer. Quantitatively, CR, CNR, and GCNR values of Deep BF were slightly improved compared to the existing methods.

2) Reconstruction results on in vivo dataset: To further validate the performance gain on fully-sampled data, in Fig. 5 we showed the results of two in vivo examples for fully-sampled data. The images are generated using standard DAS, MVBF and the proposed DeepBF method. In Fig. 5 it can be easily seen that our method provides comparable visual quality compared to DAS and MVBF methods. Interestingly, it is remarkable that the CR, CNR and GCNR values are significantly improved by the DeepBF. To investigate the origin of the quantitative improvement, we showed the magnified views as inset in Fig. 5.
there are several artifacts around the wall of anechoic regions in DAS and MVBF methods, which can be confused with structure. On the other hand, those artifacts are not visible in DeepBF, which makes the visual quality of the US images and quantitative values higher compared to DAS and MVBF methods.

B. Compressive beamforming

1) Reconstruction results on phantom dataset: Fig. 6 show the results of an phantom example for 32, 16, and 4 Rx-channels down-sampling schemes on random sampling scheme. Since 64 channels are used as a full sampled data, this corresponds to the full data as well as subsampled data with $2 \times$, $4 \times$, and $16 \times$ sub-sampling factors. The images are generated using the proposed DeepBF, MVBF and the standard DAS beam-former methods. Our method significantly improves the visual quality of the US images by estimating the correct structural details and eliminating artifacts caused by sub-sampling. The residual of fully-sampled and sub-sampled images are shown in pseudo colors on normalized scale. From the difference images it can be easily seen that unlike DAS and MVBF, in DeepBF there is a graceful degradation in quality of images. Note that the proposed method successfully reconstructed both the near and the far field regions with equal efficacy, and only minor structural details are imperceivable in sub-sampled images. Note that the training data consist of only in vivo carotid scans; but relative improvement in diverse test scenarios is nearly the same for both in vivo and phantom cases. This shows the generalization power of the proposed method.

2) Reconstruction results on in vivo dataset: Fig. 7 illustrates representative examples of in vivo data at $2 \times$, $4 \times$, and $16 \times$ acceleration. By harnessing the spatio-temporal (multi-depth and multi-line) learning, the proposed CNN-based beamformer successfully reconstructs the images with good quality in all down-sampling schemes. From residual images it can be seen that in contrast to DAS and MVBF, there is a graceful degradation in quality of images in DeepBF. Overall image quality by the proposed DeepBF maintains good visual quality at even at highest sub-sampling rate. Unlike DAS and MVBF, DeepBF preserves the original structural details as well as the contrast of the sub-sampled data much closer to the fully-sampled image.

C. Quantitative comparison

We also compared the CR, CNR, GCNR, PSNR, and SSIM distributions of reconstructed B-mode images of in vivo and phantom test datasets.

Table II shows the comparison of DAS, MVBF and proposed DeepBF method on 360 in vivo test frames for random sub-sampling scheme. In terms of CR, CNR and GCNR, the overall performance of DAS and MVBF were relatively similar. However, the results by the proposed method are significantly superior to those of DAS and MVBF. Here, to investigate the performance degradation with respect to the sub-sampling, we also calculated the PSNR and SSIM values with respect to the results of the full scan using our own methods. Again, the performance degradation in terms of
Fig. 7. Comparison of various beamformers for in vivo data with random sub-sampling patterns. The images are shown in the same window level (0 $\sim$ −60 dB for the beamformed images, and 0 $\sim$ 1 for the difference images.)

PSNR and SSIM was more graceful by the proposed DeepBF especially at low subsampling factors.

In Fig. 8, we provides distribution plots for various performance measures for phantom test dataset. In fully sampled case, our DeepBF shows overall gain of around 1.23 dB in CR, and 0.07 units improvement in CNR compared to DAS. In sub-sampling cases, unlike DAS and MVBF in which the performance is highly sensitive to the rate of sampling, the proposed DeepBF shows consistent performance even at 4× reduced sampling rate. This can be easily seen in Fig. 8 (third column), where in random sampling case the average value of GCNR remain constant at 0.90 units for 1× to 4× sampling factors and only drop by 0.03 and 0.04 units at 8× and 16× sampling factors respectively.

The CR, CNR, and GCNR, are the measure for local regions, whereas the PSNR and SSIM are the global metric. To calculate the PSNR and SSIM, images generated using 64 Rx-channels were considered as reference images for all algorithms. As shown in Fig. 8 the proposed method shows significantly higher PSNR and SSIM values, confirming that the proposed method successfully recover actual structural detail in sub-sampled images.

D. Computational time

One big advantage of ultrasound image modality is it runtime imaging capability, which require fast reconstruction time. Although training required 40 hours for 200 epochs using MATLAB, once training was completed, the reconstruction
time for the proposed deep learning method is not very long. The average reconstruction time for each depth planes is around 4.8 (milliseconds), which could be easily reduce by optimized implementation and reconstruction of multiple depth planes in parallel.

VI. DISCUSSION

In Fig 9, we compared lateral and axis profiles through the center of the a phantom anechoic cysts using DAS and proposed DeepBF methods. In particular, an anechoic cysts of 6mm diameter scanned from the depth of 52mm and B-mode images were obtained for full data as well as random sampling with 2× and 16× sub-sampling factors using DAS and proposed DeepBF. From the figures it can be seen that under all sampling schemes, on the boundary of cysts the proposed method show sharp changes in the pixel intensity with respect to the lateral position in the image. Although the axial profile shows similar trend to DAS for all subsampling rates, there are significant gain in lateral resolution by the proposed DeepBF compared to its DAS counterparts. The different resolution improvement between lateral and axial directions in the proposed method may be due to our training scheme which uses RF data from all depth as training data. The depth dependent training scheme may be a solution for this, which will be investigated in other publications.

Note that our CNN is trained on full sampled (64-Rx) data, but surprisingly lateral resolution in DeepBF images is much better than the (64-Rx) images obtained from standard DAS method. This super resolution effect is prominent for all sub-sampling factors. This is consistent with our observation on the CR, CNR and GCNR improvement on full sampled data. We believe that this may be originated from the synergistic combination from multiple data sets, as shown in our recent work [46]. Note that this synergistic boosting is not possible from analytic form of standard DAS beamformer. The proposed multi-line, multi-depth method is also compared different design choices on phantom data for variable subsampling case. The results clearly show that the proposed method with end-to-end learning to generate IQ data with the combination of training with multiple subsampling rates and multiple depths, provided the best quantitative values.

We also compared our method with Deep RF interpolation method [27]. Again, the proposed method also outperform the Deep RF interpolation method [27]. Fig 10 shows reconstruction results of various methods at 4× subsampling rate, which is compared with the full data reconstruction. The contrast of the Deep BF, especially at anechoic regions, are very close to the full sampled case, whereas the other methods generates artifacts like patterns. Quantitatively, for 4× sub-sampled in vivo test dataset, the Deep RF interpolation [27] achieves CNR, GCNR, PSNR, and SSIM values of 1.31, 0.63 units, 22.15 dB and 0.82 units, which are 0.07, 0.02 units, 1.4 dB and 0.05 units inferior to the proposed method respectively. Here we would like to point out that, in [27], deep learning approach was designed for interpolating missing RF data, which are later used as input for standard beamformer. On the other hand, the proposed method is an end-to-end CNN-based beamforming pipeline, without requiring additional beamformer. Consequently, this approach is much simpler and can be easily incorporated to replace the standard beamforming pipeline.

VII. CONCLUSION

In this paper, we presented a novel deep learning-based adaptive and compressive beamformer to generate high-quality
B-mode ultrasound image. The proposed method is purely a data-driven method which exploits the spatio-temporal redundancies in the raw RF data, which help in generating improved quality B-mode images using various transducer numbers. The proposed method improved the contrast of B-mode images by preserving the dynamic range and structural details of the RF signal in both the phantom and in vivo scans. Therefore, this method can be an important platform for ultrasound imaging.

## References

[1] F. Viola and W. F. Walker, “Adaptive signal processing in medical ultrasound beamforming,” in *IEEE Ultrasonics Symposium*, 2005, vol. 4, Sep. 2005, pp. 1980–1983.

[2] J. Capon, “High-resolution frequency-wavenumber spectrum analysis,” *Proceedings of the IEEE*, vol. 57, no. 8, pp. 1408–1418, Aug 1969.

[3] F. Vignon and M. R. Burcher, “Capon beamforming in medical ultrasound imaging with focused beams,” *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 55, no. 3, pp. 619–628, March 2008.

[4] K. Kim, S. Park, J. Kim, S. Park, and M. Bae, “A fast minimum variance beamforming method using principal component analysis,” *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 61, no. 6, pp. 930–945, June 2014.

[5] W. Chen, Y. Zhao, and J. Gao, “Improved capon beamforming algorithm by using inverse covariance matrix calculation,” in *IET International Radar Conference 2013*, April 2013, pp. 1–6.

[6] C. C. Nilsen and I. Hafizovic, “Beamspace adaptive beamforming for ultrasound imaging,” *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 56, no. 10, pp. 2187–2197, October 2009.

[7] A. M. Deyst and B. M. Asl, “A fast and robust beamspace adaptive beamformer for medical ultrasound imaging,” *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 64, no. 6, pp. 947–958, June 2017.

[8] A. C. Jensen and A. Austeng, “An approach to multibeam covariance matrices for adaptive beamforming in ultrasonography,” *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 59, no. 6, pp. 1139–1148, June 2012.

[9] ——, “The iterative adaptive approach in medical ultrasound imaging.” *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 61, no. 10, pp. 1688–1697, Oct 2014.

[10] E. Kang, J. Min, and J. C. Ye, “A deep convolutional neural network using directional wavelets for low-dose x-ray CT reconstruction,” *Medical Physics*, vol. 44, no. 10, 2017.

[11] E. Kang, W. Chang, J. Yoo, and J. C. Ye, “Deep convolutional framelet denoising for low-dose CT via wavelet resilient network.” *IEEE Transactions on Medical Imaging*, vol. 37, no. 6, pp. 1358–1369, 2018.

[12] H. Chen, Y. Zhang, W. Zhang, K. Li, J. Zhou, and G. Wang, “Low-dose CT via convolutional neural network.” *Biomedical Optics Express*, vol. 8, no. 2, pp. 679–697, 2017.

[13] J. Adler and O. Öktem, “Learned primal-dual reconstruction,” *IEEE Transactions on Medical Imaging (in press)*, 2018.

[14] J. M. Wolterink, T. Leiner, M. A. Viergever, and I. Sgour, “Generative adversarial networks for noise reduction in low-dose CT,” *IEEE Transactions on Medical Imaging*, vol. 36, no. 12, pp. 2536–2545, 2017.

[15] K. H. Jin, M. T. McCann, E. Froustey, and M. Unser, “Deep convolutional neural network for inverse problems in imaging,” *IEEE Transactions on Image Processing*, vol. 26, no. 9, pp. 4509–4522, 2017.

[16] Y. Han and J. C. Ye, “Learning-Net via deep convolutional framelets: Application to sparse-view CT,” *IEEE Transactions on Medical Imaging*, vol. 37, no. 6, pp. 1418–1429, 2018.

[17] S. Wang, Z. Su, L. Ying, X. Peng, S. Zhu, F. Liang, D. Feng, and D. Liang, “Accelerating magnetic resonance imaging via deep learning,” in *Biomedical Imaging (ISBI), 2016 IEEE 13th International Symposium on*. IEEE, 2016, pp. 514–517.

[18] K. Hampam, T. Klaczer, E. Kobler, M. P. Recht, D. K. Sodickson, T. Pock, and F. Knoll, “Learning a variational network for reconstruction of accelerated MRI data.” *Magnetic resonance in medicine*, vol. 79, no. 6, pp. 3055–3071, 2018.

[19] J. Schlemper, J. Caballero, J. V. Hajnal, A. N. Price, and D. Rueckert, “A deep cascade of convolutional neural networks for dynamic MR image reconstruction,” *IEEE Transactions on Medical Imaging*, vol. 37, no. 2, pp. 491–503, 2018.

[20] B. Zhu, J. Z. Liu, S. F. Cauley, B. R. Rosen, and M. S. Rosen, “Image reconstruction by domain-transform manifold learning,” *Nature*, vol. 555, no. 7697, p. 487, 2018.

[21] D. Lee, J. Yoo, S. Tak, and J. Ye, “Deep residual learning for accelerated MRI using magnitude and phase networks,” *IEEE Transactions on Biomedical Engineering*, 2018.

[22] D. Allman, A. Reiter, and M. A. L. Bell, “A machine learning method to identify and remove reflection artifacts in photoacoustic channel data,” in *2017 IEEE International Ultrasonics Symposium (IUS)*, Sept 2017, pp. 1–4.

[23] A. C. Luchies and B. C. Byram, “Deep neural networks for ultrasound beamforming,” *IEEE transactions on medical imaging*, vol. 37, no. 9, pp. 2010–2021, 2018.

[24] M. Feingold, D. Freedman, and B. W. Anthony, “A deep learning framework for single sided sound speed inversion in medical ultrasound,” arXiv preprint arXiv:1810.00322, 2018.

[25] M. Perdios, A. Besson, M. Marzetti, and J. P. Thiran, “A deep learning approach to ultrasound image recovery,” in *2017 IEEE International Ultrasonics Symposium (IUS)*. IEEE, 2017, pp. 1–4.

[26] Z. Zhou, Y. Wang, J. Yu, Y. Guo, W. Guoand, and Y. Qi, “High spatial-temporal resolution reconstruction of plane-wave ultrasound images with a multichannel multiscale convolutional neural network.” *IEEE transactions on ultrasonics, ferroelectrics, and frequency control*, 2018.

[27] Y. Han, T. Li, S. Khan, J. Hinam, C. Ye et al., “Efficient b-mode ultrasound image reconstruction from sub-sampled rf data using deep learning.” *IEEE transactions on medical imaging*, 2018.

[28] M. Gasse, F. Millioz, E. Roux, D. Garcia, H. Liebgott, and D. Friboulet, “High-quality plane wave compounding using convolutional neural networks.” *IEEE transactions on ultrasonics, ferroelectrics, and frequency control*, vol. 64, no. 10, pp. 1637–1639, 2017.

[29] O. Seneuf, S. Vedula, G. Zarakhov, A.Bronstein, M. Zibulevsy, O. Michailovich, D. Adam, and D. Blondein, “High frame-rate cardiac ultrasound imaging with deep learning.” *in Medical Image Computing*
and Computer Assisted Intervention – MICCAI 2018. A. F. Frangi, J. A. Schnabel, C. Davatzikos, C. Alberola-López, and G. Fichtinger, Eds. Cham: Springer International Publishing, 2018, pp. 126–134.

[30] S. Vedula, O. Senouf, G. Zurakhow, A. Bronstein, M. Zibulevsky, O. Michailovich, D. Adam, and D. Gaitini, “High quality ultrasonic multi-line transmission through deep learning,” in Machine Learning for Medical Image Reconstruction, F. Knoll, A. Maier, and D. Rueckert, Eds. Cham: Springer International Publishing, 2018, pp. 147–155.

[31] J. C. Ye and W. K. Sung, “Understanding geometry of encoder-decoder CNNs,” in Proceedings of the 36th International Conference on Machine Learning, ser. Proceedings of Machine Learning Research, K. Chaudhuri and R. Salakhutdinov, Eds., vol. 97. Long Beach, California, USA: PMLR, 09–15 Jun 2019, pp. 7064–7073.

[32] J. C. Ye, Y. Han, and E. Cha, “Deep convolutional framelets: A general deep learning framework for inverse problems,” SIAM Journal on Imaging Sciences, vol. 11, no. 2, pp. 991–1048, 2018.

[33] S. Khan, J. Huh, and J. C. Ye, “Universal deep beamformer for variable rate ultrasound imaging,” arXiv preprint arXiv:1901.01706, 2019.

[34] B. Luijten, R. Cohen, F. J. de Bruijn, H. A. W. Schmeitz, M. Mischi, Y. C. Eldar, and R. J. G. van Sloun, “Deep learning for fast adaptive beamforming,” in ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), May 2019, pp. 1333–1337.

[35] D. H. Brandwood, “A complex gradient operator and its application in adaptive array theory,” IEE Proceedings F - Communications, Radar and Signal Processing, vol. 130, no. 1, pp. 11–16, February 1983.

[36] Z. Chen, A. Basarab, and D. Kouamé, “Compressive deconvolution in medical ultrasound imaging,” IEEE transactions on medical imaging, vol. 35, no. 3, pp. 696–701, 2015.

[37] J. A. Jensen, “Deconvolution of ultrasound images,” Ultrasonic imaging, vol. 14, no. 1, pp. 1–15, 1992.

[38] M. O’Donnell, E. Jaynes, and J. Miller, “Kramers–Kronig relationship between ultrasonic attenuation and phase velocity,” The Journal of the Acoustical Society of America, vol. 69, no. 3, pp. 696–701, 1981.

[39] A. Vedaldi and K. Lenc, “Matconvnet: Convolutional neural networks for matlab,” in Proceedings of the 23rd ACM international conference on Multimedia. ACM, 2015, pp. 689–692.

[40] X. Glorot and Y. Bengio, “Understanding the difficulty of training deep feedforward neural networks,” in Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics, 2010, pp. 249–256.

[41] J. F. Synnevåg, A. Austeng, and S. Holm, “Adaptive beamforming applied to medical ultrasound imaging,” IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 54, no. 8, pp. 1606–1613, August 2007.

[42] R. M. Rangayyan, Biomedical Image Analysis, ser. Biomedical Engineering, M. R. Neuman, Ed. Boca Raton, Florida: CRC Press, 2005.

[43] A. Rodriguez-Molares, O. M. H. Rindal, J. D’hooge, S.-E. Måsøy, A. Austeng, and H. Torp, “The generalized contrast-to-noise ratio,” 2018.

[44] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: from error visibility to structural similarity,” IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600–612, April 2004.

[45] O. M. H. Rindal, A. Austeng, H. Torp, S. Holm, and A. Rodriguez-Molares, “The dynamic range of adaptive beamformers,” in 2016 IEEE International Ultrasonics Symposium (IUS), Sep. 2016, pp. 1–4.

[46] E. Cha, J. Jang, J. Lee, E. Lee, and J. C. Ye, “Boosting CNN beyond label in inverse problems,” arXiv preprint arXiv:1906.07330, 2019.