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Universal Plane-Wave Compounding for High Quality US Imaging Using Deep Learning

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***Abstract*—Plane-wave compounding is to sum up several successive plane waves incident at different angles to form an image. By applying time-reversal of the received signals, transmit focusing can be synthesized. Unfortunately, to improve the temporal resolution, the number of plane waves should be reduced, which often degrades the image quality. To address this problem, an image domain learning method using neural networks has been proposed, but the network needs to be retrained when the number of plane waves changes. Herein, we propose, for the first time, a universal plane-wave compounding scheme using deep learning to directly process plane waves and RF data acquired at different view angles and sub-sampling rate to generate high quality US images.**

***Index Terms*—Ultrafast ultrasound, planewave imaging (PWI), plane wave compounding, deep learning, beamforming**

I. Introduction

In planewave imaging (PWI) ultrasound, multiple low quality images are acquired with different incident angles, and with the help coherent compounding, a single high quality image is formed from these low quality images. Although number of planewaves (PWs) required for high quality image is typically smaller than the number of scanlines in focused mode scanning, the memory utilization and associated power consumption is relatively higher than the focused mode imaging [1]. One way of reducing the data is to skip acquisitions at some angles to improve temporal resolution at the cost of spatial resolution. Unfortunately, standard compounding methods produce degraded quality images when the number of plane wave is not sufficient, which make it unsuitable for clinical applications.

Although a low cost compressive sensing based method was proposed in [2], the results were shown on the limited number of simulation data only, and we found that the algorithm often produces inferior results compared to conventional coherent plane-wave compounding (CPC) method. To achieve reasonable performance to complexity ratio, a variety of deep learning methods have been recently proposed that are specifically trained for particular acquisition scenario [3], [4]. Herein, by properly exploiting the spatio-temporal redundancy in PW-depth-channels cube, we propose a convolutional neural network (CNN) based plane wave compounding method called (DeepPWI) that generates high quality images for various imaging configurations. The major contributions of this work are as follows:

- A single universal model is proposed for variety of sub-sampling schemes such as uniform PW sub-sampling or random sub-sampling of RF data.
- The proposed model is evaluated for real measurements on both phantom and *in-vivo* scans.
- The performance of proposed method is evaluated on large number of scans using standard and recently proposed quality measure such as generalized contrast-to-noise-ration (GCNR) [5].

II. Proposed Method

To design a deep learning based CPC method, we consider a set of fully-sampled RF measurements defined as $F \in \mathbb{R}^{x\times y\times z}$, where x, y, z represents the number of depth planes, the length of RF signals, and the number of planewaves, respectively. Then, in the conventional CPC methods, z number of low-resolution beamformed RF images are compounded to produce a high-quality RF image, $I \in \mathbb{R}^{x\times y}$. Our objective is to estimate I using RF and plane-wave subsampled measurements $S \in \mathbb{R}^{x\times m\times n}$. Here, $m < y$ is reduced length of RF signal and $n < z$ is reduced number of planewaves, respectively. Since we are interested in designing a universal deep model for all sampling patterns, we choose to use a fixed size input signal $T \in \mathbb{R}^{x\times y\times z}$, where subsampled measurement data S is padded with zeros to adjust the size. Identification of optimal compounding function is possible by identifying the Θ-parameterized model $\mathcal{Q}_\Theta$ such that $I = \mathcal{Q}_\Theta(T)$ produces the least empirical loss for the training data.

We propose to estimate compounding model $\mathcal{Q}_\Theta$ with convolutional neural network. Although deep learning models are typically assumed as black-boxes, this black-box approach limits their applications for medical applications where discrimination between measurement artifacts and actual abnormalities is essential for the diagnosis purposes. In contrast to these blackbox approaches, in this study we used the design strategy which is mathematically plausible. In particular, we used the design approach based on our recent study [6], where we found that an encoder-decoder CNN with ReLU non-linearity and skip connections generates large number of

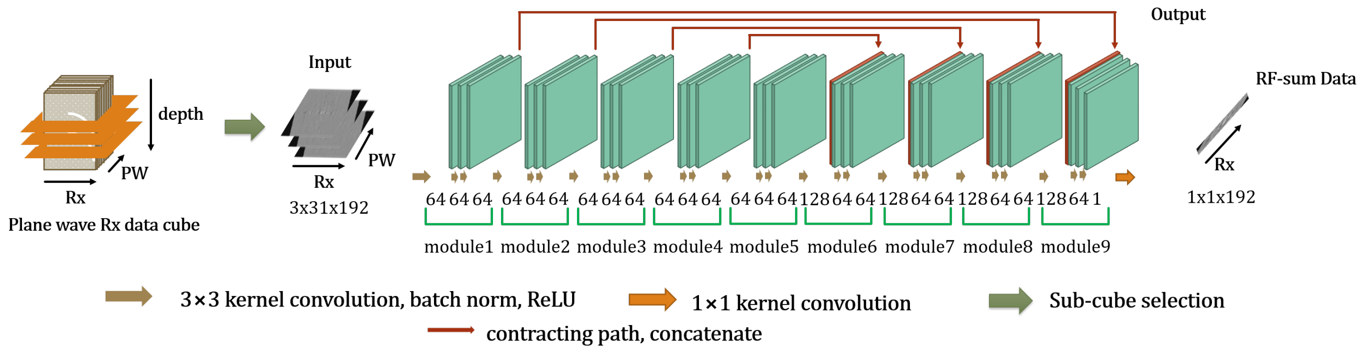

Fig. 1. Schematic diagram of the proposed convolutional neural network (CNN) based planewave reconstruction system

distinct non-overlapping regions where input for each region shares the common linear representation. This piecewise linear approximation of the mapping allows the CNN to switch to the corresponding linear representation instantaneously depending on the input data, and this property is suitable for adaptive plane wave compounding scheme by effectively reconstructing images for variety of sub-sampling schemes. Therefore, our DeepPWI neural network can be trained to estimate the filters Θ by solving the following optimization problem:

$$\min_{\Theta} \sum_{i=1}^{N} \|v^{a(i)} - \mathcal{Q}_{\Theta} z^{(i)}\|_2^2 \tag{1}$$

where $\mathcal{Q}$ is the composite representation of deconvolution filters and compounding weights, $\{(z^{(i)}, v^{a(i)})\}_{i=1}^{N}$ denotes the training data set composed of RF data and the target data at a specific depth, which are collected across all depth, subjects and sub-sampling patterns.

In this study the proposed CNN model consist of 27 layers each comprises of convolution, batch normalization, ReLU, and skip connections. The detailed block diagram of proposed method is shown in Fig. 1. The CNN takes 3 adjacent depth planes to generate central depth vector. By sequentially processing the sub-sampled data-cube a high-quality image can be generated. The model is implemented using MatConvNet [7] in the MATLAB 2015b environment. To optimize the learning parameter, the model is trained using stochastic gradient descent algorithm by varying the learning rate from 10-3 to 10-5 in 200 epochs.

For experimental verification, 100 phantom, and 100 *in-vivo* samples are acquired from the ATS-539 phantom and the carotid area of 10 volunteers, using the E-CUBE 12R US system with L3-12H linear array transducer on 8.48 MHz center frequency. For training purpose, RF data of only 8 *in-vivo* frames (images) were used. Each US image, the raw data have depth ranges between $25-60$ mm and consist of 31 PWs and 192-channels. For quantitative evaluation we used two sampling schemes: (1) uniform sub-sampling of PW images, to improve temporal resolution, and (2) random sub-sampling of RF data to reduce power consumption. In particular, for PW sub-sampling experiment, we generated four input subsets each consist of 31, 11, 7 or 3 PWs. In random sub-sampling scheme, RF data is randomly sub-sampled and missing data is replaced by zero padding. In particular we generated four input subsets each with 1, 2, 4 and 8 times sub-sampled data. For both sampling schemes, the target label data for training were obtained using conventional CPC method with fully-sampled 31 PWs.

III. Results and Discussion

The trained model is evaluated using peak-signal-to-noise ratio (PSNR) and the recently proposed generalized contrast-to-noise ratio (GCNR) [5] measure. In particular, the scale of GCNR with the ranges of $[0, 1]$ is very intuitive and easy to interpret, where 0 represents no contrast and 1 represents the maximum contrast. Fig. 2 show the quantitative comparison results in terms of GCNR for *in-vivo* and phantom examples on different sub-sampling patterns. We found that the proposed method effectively improves the contrast of the sub-sampled data. Interestingly, for *in-vivo* case, the GCNR results by the proposed method did not drop even with only 7 PWs or $4\times$ down-sampling, and the performance drop was small even for extremely high sub-sampling rates i.e., for 3 PWs and $8\times$ down-sampling. For phantom data case, we also observed graceful performance degradation and the relative gain in GCNR was almost same as in *in-vivo* case. It is noteworthy to point-out that a single CNN model is used for the reconstruction in all sub-sampling scenarios and no additional training is performed for particular datatype (phantom/*in-vivo*) or sampling patterns.

Fig. 3 show example results from *in-vivo* and phantom scans. The images are generated using CPC and the proposed DeepPWI methods using fully sampled and sub-sampled data. In particular, for sub-sampled case, we compared PW down-sampling cases with only three PWs and $8\times$ random RF sub-sampling results. For the calculation of GCNR two regions are selected as highlighted with yellow and blue circles in Fig. 3. The same regions are magnified for better visualization. All images are shown for 40mm axial depth on the dynamic range of 60 dB scale.

Fig. 3(a) show reconstruction results on *in-vivo* data from carotid region. The proposed method successfully recovers the detailed anatomical features in sub-sampled images, where conventional compounding method generates images with the washout artifact. This improvement is quantified using PSNR and GCNR measures. In particular, we achieved 0.56dB and 4.13dB PSNR gain in PW and RF sub-sampling schemes, respectively. The similar trend is observed in GCNR performance, where proposed algorithm show 0.93 and 0.94 units GCNR which is 3% and 14% higher than the conventional method. Besides, our universal model also works well with fully sampled data and produces very high PSNR of 35.81dB. This similarity is also visible in GCNR results. These observations in Fig. 3(a) coincides with the quantitative results in Fig. 2(top).

In Fig. 3(b), the similar performance improvement was observed by the proposed method for both fully sampled data, and PW/RF sub-sampled cases. It is worthy to note that although the model is trained on *in-vivo* Carotid data it learns to produce high quality images even for sub-sampled phantom dataset. For example, in Fig. 3(b), for the case of PW sub-sampling case, CPC method generates very dark image, which indicates the loss of dynamic range due to high sub-sampling rate. However, the proposed DeepPWI method produces significantly improved quality image with 18.14dB PSNR and 0.73 units GCNR i.e., 6.73dB, and 1% higher than the CPC method, respectively. Similarly, for $8\times$ random RF sub-sampling case, our reconstruction results coincides with the quantitative results in Fig. 2(bottom). In particular, proposed DeepPWI method achieve 23.52dB PSNR and 0.69 units GCNR score, which is 2.19dB and 13% higher than the conventional CPC method. It shows that the overall performance gain achieved using the proposed method is robust to the sub-sampling patterns; moreover, it is insensitive to particular datatype.

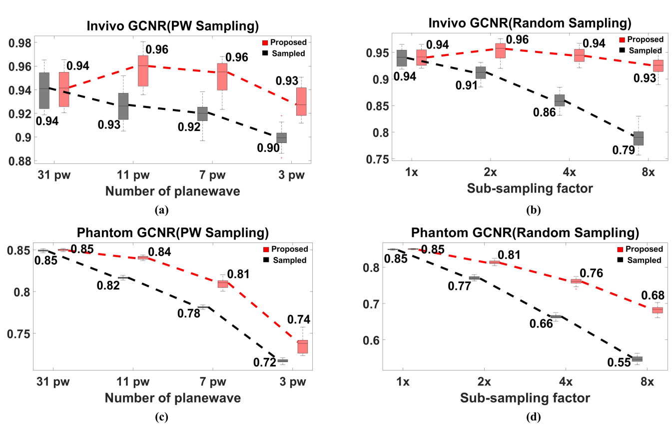

Fig. 2. B-Mode images from *in-vivo* data of carotid region (top), and from tissue mimicking phantom (bottom)

IV. Conclusion

In this research, we presented a purely data-driven method for plane wave compounding in ultrasound images. The proposed method exploits the spatio-temporal redundancies in the raw RF data to generate improved quality B-mode images

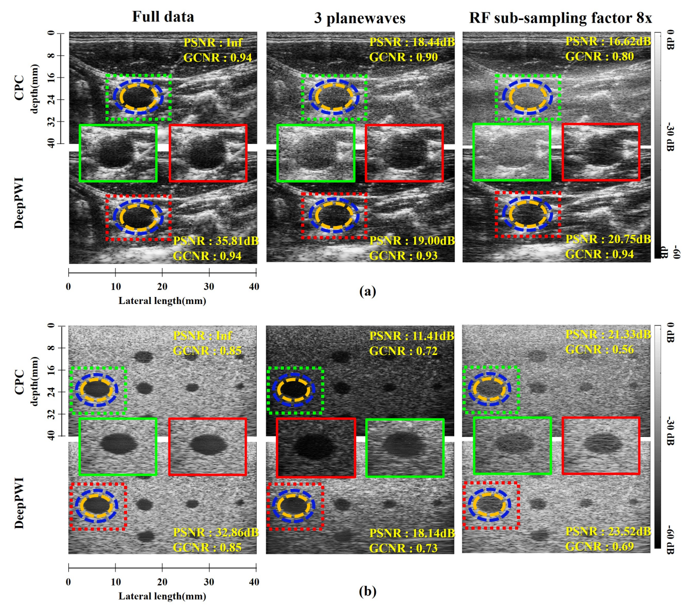

Fig. 3. B-Mode images from *in-vivo* data of carotid region (top), and from tissue mimicking phantom (bottom)

using fewer Rx channels or planewave images. Furthermore, the network was also used for the fully sampled RF data to significantly improve the image contrast and resolution. The proposed neural network-based reconstruction approach is robust and suitable for various sub-sampling patterns. The proposed model is shown achieve significant improvement over sub-sampled data for both the phantom and the *in-vivo* scans. Therefore, this method can be an important platform for accelerated planewave US imaging.

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