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Muyinatu A. Lediju Bell, "Applications of ultrasound image formation in the deep learning age," Proc. SPIE 12204, Emerging Topics in Artificial Intelligence (ETAI) 2022, 1220403 (3 October 2022); doi: 10.1117/12.2631614

Event: SPIE Nanoscience + Engineering, 2022, San Diego, California, United States

Invited Paper

Applications of Ultrasound Image Formation in the Deep Learning Age

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ABSTRACT

Historically, there are many options to improve image quality that are each derived from the same raw ultrasound sensor data. However, none of these historical options combine multiple contributions in a single image formation step. This invited contribution discusses novel alternatives to beamforming raw ultrasound sensor data to improve image quality, delivery speed, and feature detection after learning from the physics of sound wave propagation. Applications include cyst detection, coherence-based beamforming, and COVID-19 feature detection. A new resource for the entire community to standardize and accelerate research at the intersection of ultrasound beamforming and deep learning is summarized (https://cubdl.jhu.edu). The connection to optics with the integration of ultrasound hardware and software is also discussed from the perspective of photoacoustic source detection, reflection artifact removal, and resolution improvements. These innovations demonstrate outstanding potential to combine multiple outputs and benefits in a single signal processing step with the assistance of deep learning.

1. INTRODUCTION

Ultrasound is ubiquitous and has many benefits, including being safe, portable, and cost-effective, as well as offering real-time anatomical views for diagnostic decisions and surgical or interventional guidance. Despite these benefits, ultrasound images suffer from several outstanding challenges that have persisted in its 60+ year history. For example, ultrasound images are known to be noisy, contain a granular texture appearance known as speckle, and they may suffer from acoustic clutter, sound attenuation, and poor resolution at depth. As a result of these challenges, ultrasound images can be difficult to segment and overall difficult to interpret.

Techniques implemented to overcome these challenges include spatial compounding, which addresses speckle by smoothing out tissue texture.[1,2] Doppler imaging[3,4] enhances blood flow and could be an approach to vessel segmentation. Harmonic imaging[5,6] enables the reduction of acoustic clutter, although this clutter reduction benefit is not realized in some cases, particularly for patients who are overweight or obese. Coherence-based beamforming[7–9] effectively reduces clutter in cases where harmonic imaging fails. However, the originally proposed algorithm is computationally expensive to implement.[10] Elasticity imaging[11–13] visualizes the mechanical properties of tissues and could be an approach to tumor segmentation. Additional techniques not summarized in this paragraph also exist to provide similar benefits to those summarized above.

Although each technique described above can be effective at addressing one of the noted challenges, none simultaneously address multiple challenges in a single image formation step. Yet, all advances noted above are derived from the same raw ultrasound data to make images. This conundrum motivates a rethinking of the image formation process to determine if multiple challenges can be addressed in a single signal processing step.

My lab is exploring deep learning as a potential solution to provide multiple outputs from a single input of raw ultrasound channel data (also referred to as raw ultrasound sensor data), thereby addressing multiple

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Emerging Topics in Artificial Intelligence (ETAI) 2022, edited by Giovanni Volpe, Joana B. Pereira, Daniel Brunner, Aydogan Ozcan, Proc. of SPIE Vol. 12204, 1220403 · © 2022 SPIE · 0277-786X · doi: 10.1117/12.2631614

challenges in a single step. Section 2 describes four deep learning applications that have the potential to serve as solutions to multiple ultrasound image formation challenges (i.e., cyst detection and segmentation, coherence-based beamforming, COVID-19 feature detection, benchmark resources for the entire community). Section 3 concludes with a summary and outlook that also connects ultrasound applications to optics and photonics by describing related photoacoustic approaches to deep learning from raw ultrasound sensor data.

2. APPLICATIONS

2.1 Cyst Detection and Segmentation

Fig. 1 summarizes the evolution of deep neural networks (DNNs) developed to input raw channel data and output human-readable images for the task of cyst detection and segmentation.[14–19] Each gray text in the figure highlights novelty in comparison to the preceding approach. In each case, we trained with simulated data, then validated the trained networks with experimental ultrasound phantom data.

We developed our first DNN to achieve multiple outputs from a single input in 2019.[16] This achievement initially relied on a generative adversarial network (GAN). We compared the GAN performance with and without the associated discriminators, as well as with multiple encoder-decoder combinations. From this comparison, we realized that one encoder and two decoders was sufficient to achieve our goal,[17] and a GAN was not necessary. Notably, moving away from the GAN produced a speckle smoothing effect, which was reminiscent of spatial compounding.[17] This smoothing was achieved in addition to producing a B-mode image simultaneously with the associated cyst segmentation.[17]

At this time, we also transitioned from raw radiofrequency (RF) data to raw in phase and quadrature data (IQ) as the DNN input.[17] This switch occurred because the IQ data requires less axial samples to achieve the same image depth. Therefore, the axial dimension was downsampled more vigorously with IQ data, and more axial information was stored in a single network input when compared to the same downsampling applied to RF data. We also changed our training approach to mask out clutter and produce clutter-free DNN images simultaneously with DNN segmentations.

With this model in place, we then moved toward extending our evaluation from experimental phantom data to ultrasound images of *in vivo* breast masses.[18] In a majority of approaches across all experimental cases, we both removed speckle and reduced clutter in addition to providing an image simultaneously with a segmentation, as illustrated in Fig. 2. We also demonstrated that inputting subaperture beamformed IQ data preserved speckle when producing a DNN image.[18] Recognizing that speckle preservation is important for some tasks, it is notable

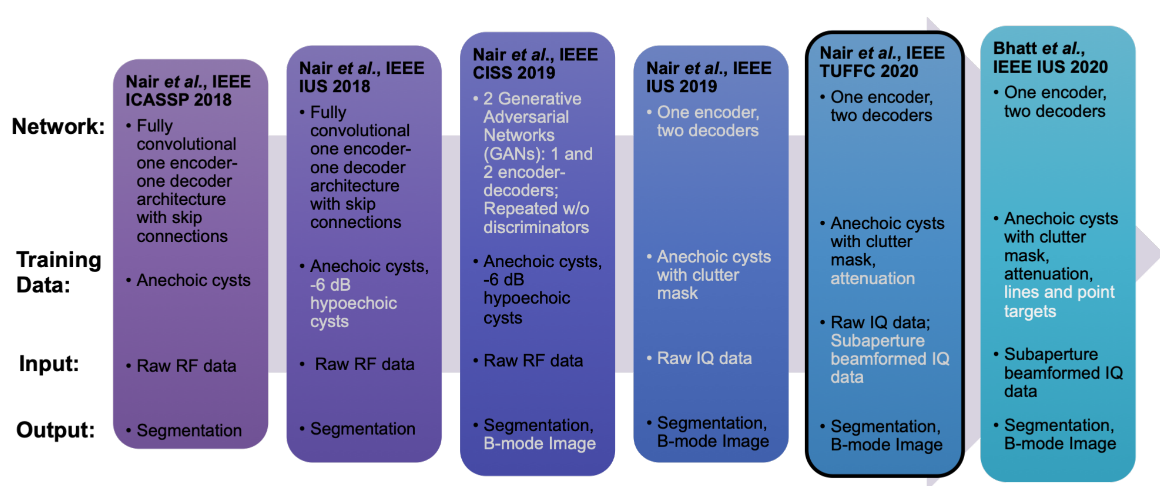

Figure 1. Evolution of deep learning networks, training data, and inputs and outputs presented by Nair *et al.*[14–18] and Bhatt *et al.*[19] Each gray text highlights the novelty in comparison to the preceding approach. The black outline highlights the paper by Nair *et al.*[18] summarized in Fig. 2.

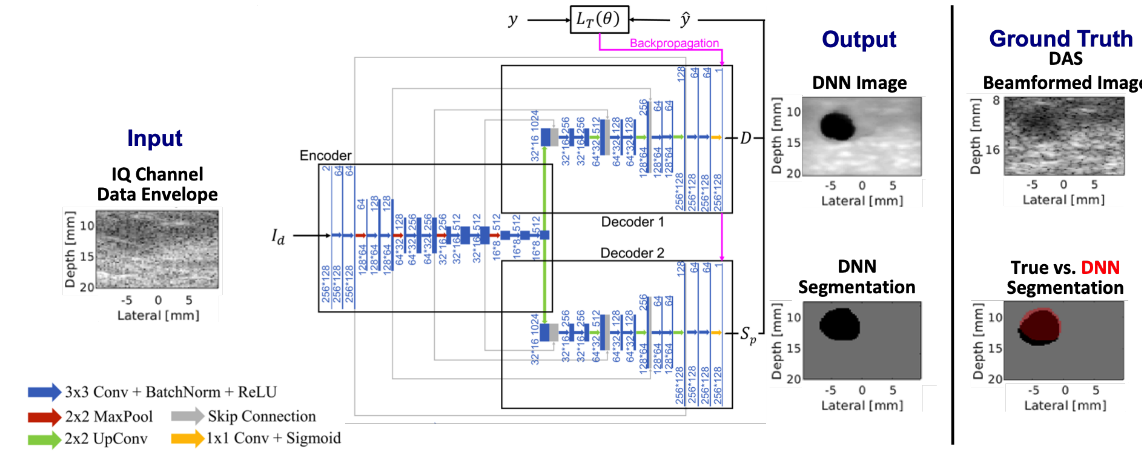

Figure 2. Two outputs from a single input of raw channed data. The DNN image output also reduces acoustic clutter and smooths the speckle appearance of tissue, offering additional beneficial outputs from a single input of raw data. Adapted from Nair *et al.*[18]

that the network architecture shown in Fig. 2 is sufficiently versatile to deliver both speckle-containing and speckle-reduced images depending on the input data type with only one change to the input layer to accept focused data and no other changes to the network architecture or training process. Finally, Bhatt *et al.*[19] demonstrated that including more features during training (i.e., lines, point targets) removed the false positives that were present in larger fields of view than that shown in Fig. 2.

In summary, this work is the first to bypass the entire beamforming process and replace it with machine learning and computer vision techniques to remove traditionally problematic noise artifacts and create a fundamentally new type of artifact-free, high-contrast, high- resolution, ultrasound-based image for guiding interventional procedures. This work is also the first to create both an ultrasound image of a feature of interest (e.g., a cyst) and a segmentation of the same feature from a single deep neural network input of raw ultrasound channel data. The ultrasound image can either contain speckle or remove speckle, based on one change to the input data type and the input network layer. The speckle-reduced image emphasizes the structure of interest (e.g., a cyst) and deemphasizes surrounding structures (e.g., tissue), which is promising for image-guided robotic tracking tasks. With combined DNN image, DNN segmentation, clutter reduction, and speckle smoothing all achieved in parallel from a single input of raw channel data, we have successfully demonstrated that it is possible to combine multiple benefits in one signal processing step with the assistance of deep learning.

2.2 Coherence-Based Beamforming

One challenge with clutter-reduced hypoechoic breast masses is that they appear with lower amplitude than surrounding tissue when using traditional delay-and-sum (DAS) beamforming as the basis for learned images. However, with the DAS beamformer, it can be difficult to distinguish fluid masses (which are typically benign) from solid masses (which could be benign or malignant). This difficulty results in false positive rates as high as 93% with ultrasound imaging alone,[21–23] benign fluid masses needing to be biopsied[23] or aspirated,[24] and solid masses with attempted aspiration that are unsuccessful.[23] There are also multiple follow up visits requested in some cases.[25,26] This uncertainty causes patient anxiety and also adds temporal and financial burdens on our healthcare system. Ideally, a benign, fluid-filled mass would be declared benign and fluid-filled at the time of the initial ultrasound exam, while solid masses would proceed to further evaluation and treatment if necessary.

Our proposed solution is to implement coherence-based beamforming.[27–31] My lab is the first to apply this approach to breast imaging, and we are the first to report the finding that this technique is useful for distinguishing solid from fluid masses at the time of the initial ultrasound exam. A reader study with five board-certified radiologists demonstrated that the introduction of coherence-based beamforming reduced the number of fluid-filled masses unnecessarily recommended for biopsy from 43.3% to 13.3%.[28]

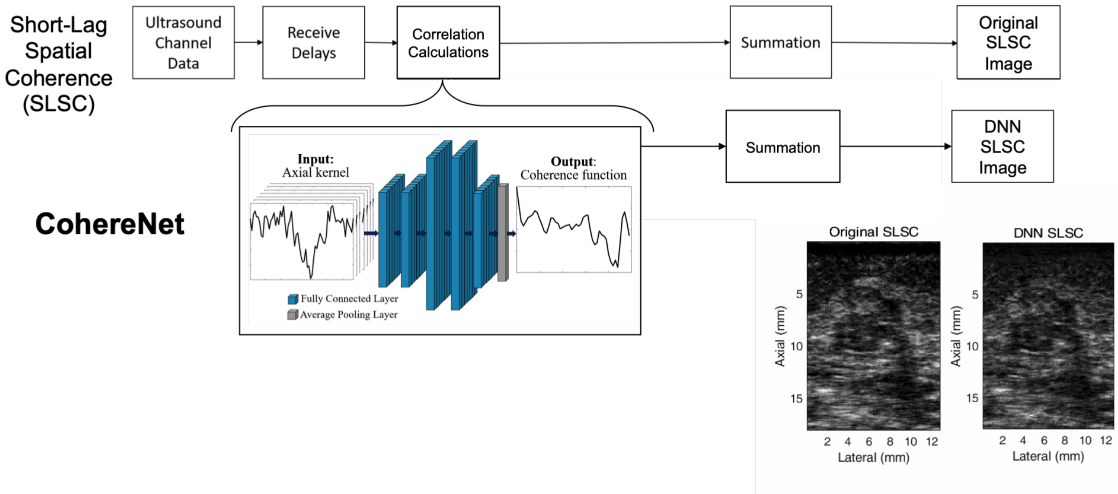

Figure 3. Deep learning approach to create spatial coherence functions for short-lag spatial coherence imaging. Adapted from Wiacek *et al.*[20]

While the coherence-based approach is advantageous for breast mass distinction, one drawback of this image formation method is the requirement for multiple cross-correlation calculations to generate each pixel in a coherence-based image, as shown at the top of Fig. 3. Therefore, my lab introduced a new deep learning approach to speed up the delivery of coherence-based images. We replaced the computationally intensive correlation calculation step with our newly developed CohereNet architecture, which contains a series of fully connected layers, as illustrated in Fig. 3. This network accepts raw ultrasound data and learns a physical property, i.e., a spatial coherence function. These learned functions are then integrated over the short-lag region to create coherence-based images. This approach creates the two pathways for short-lag spatial coherence (SLSC) image formation noted in Fig. 3 (i.e., original SLSC and DNN SLSC). The resulting two image types are highly correlated to each other, and the network also achieves our ultimate goal of processing images at a faster speed, in particular 3.4 times faster than the original algorithm that contains many coherence calculations. Notably, the DNN SLSC approach also has greater fidelity to the original algorithm when compared to the shortcuts taken to implement this algorithm with parallel programming on a graphics processing unit.[20]

In summary, this approach is the first to learn spatial coherence functions in support of forming short-lag spatial coherence images at a 3.4x faster rate than original computational approaches and with similar speed, less processing time variability, and improved image quality compared to existing parallel programming shortcuts. Clinical applications include differentiation of solid from fluid breast masses, as well as applications that fundamentally rely on cross-correlation calculations (e.g., elasticity imaging, strain imaging, and sound speed correction). This approach also creates new possibilities for hardware implementations of coherence-based beamforming in miniature (e.g., briefcase or smart phone-based) ultrasound systems, which typically have limited memory and lower-end processors.

2.3 COVID-19 Feature Detection

The role of deep learning in lung ultrasound imaging for COVID-19 detection has been summarized in several recent review articles.[33,34] Enabling details surrounding associated instrumentation has also been reviewed.[35] Since the publication of these reviews, our new work demonstrates that a similar approach to Nair *et al.*[18] can be taken to determine the best image formation stage when learning important features for COVID-19 detection. In particular, Frey *et al.*[32] demonstrated that when identifying B-line features with the U-Net implementation shown in Fig. 4, the B-mode stage was determined to be the most efficient processing stage among the four image formation stages investigated (i.e., raw IQ data, beamformed IQ data, envelope detected IQ data, and B-mode images). This finding was obtained with a systematic simulation study that incorporated multiple imaging parameters (e.g., feature amplitude, imaging depth). These DNNs were trained with simulated ultrasound data and tested on *in vivo* patient images, achieving 88% accuracy to detect the same or more B-line features than

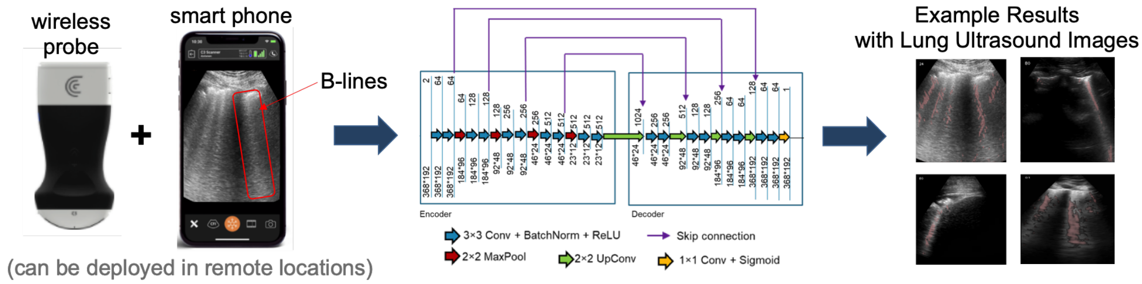

Figure 4. Deep learning approach to learn features in lung ultrasound images for COVID-19 detection. Adapted from Frey *et al.*[32]

human observers. This result is expected to assist with identifying and monitoring COVID-19, and this work is the first to investigate the performance of multiple image formation stages when detecting features in lung ultrasound images of COVID-19 patients.

2.4 Resources

Our initial success with many of the approaches described above motivated the creation of a challenge for the entire community: the Challenge on Ultrasound Beamforming with Deep Learning (CUBDL).[36–38] The four integrated CUBDL resources illustrated in Fig. 5 include: (1) the first known internationally crowd-sourced database of open-access raw ultrasound channel data (simulated, phantom, and *in vivo* data) acquired with plane wave and focused transmissions (576 acquisitions total, crowd-sourced from seven ultrasound groups around the world); (2) network descriptions and trained network weights from CUBDL winners; (3) a PyTorch DAS beamformer containing multiple components that can be converted to trainable parameters; and (4) evaluation code that integrates these multiple contributions. We also provide a data sheet of phantom sound speeds, including reported sound speeds, manufacturer data sheet sound speeds, and optimized sound speeds identified by the CUBDL organizers using the PyTorch DAS beamformer. These resources enable the field to use the same datasets and code for benchmarking of future developments. The released resources also lower barriers to entry

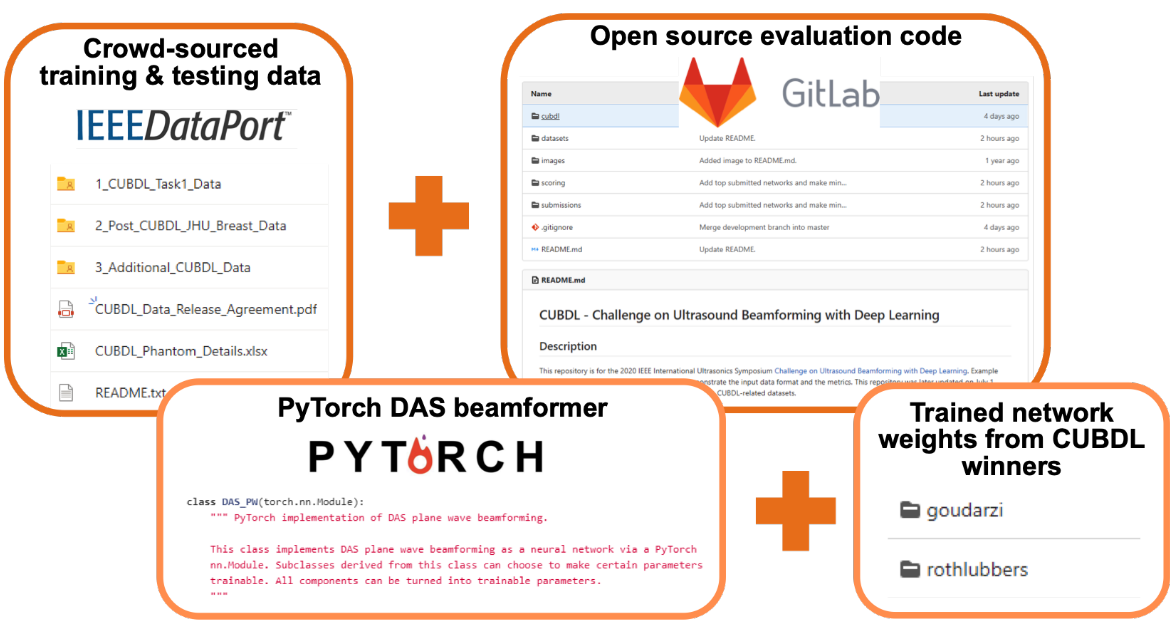

Figure 5. Summary of CUBDL resources. More details available in reports by Bell *et al.*[36] and Hyun *et al.*[37] Image source: https://cubdl.jhu.edu/results/.

into an otherwise highly specialized field, which is one effective method to increase the diversity of contributors and contributions to beamforming in the deep learning age.

3. SUMMARY AND OUTLOOK

The goal of achieving multiple outputs (e.g., simultaneous speckle smoothing, clutter reduction, image formation, image segmentation) from a single input was successfully demonstrated by Nair *et al.*[17,18] In addition, one could also conceive of concatenating multiple networks in parallel to achieve this same goal. This is particularly true if all networks receive the same type of raw ultrasound channel data. These software-based achievements may also be integrated with the next generation of ultrasound hardware, including deep learning merged with beamforming for flexible array transducers.[39]

When merging ultrasound imaging technology with optics and photonics to create photoacoustic imaging systems, which utilize the same sensing hardware as ultrasound systems,[40] similar possibilities exist.[41,42] In particular, the raw sensor data may be input to a deep neural network to learn photoacoustic source position information[43] (e.g., needle tips,[43–45] cardiac catheter tips[45–47]), to remove reflection artifacts,[44,45,47] and to improve resolution at depth.[41,44–47] In addition, the source position coordinates learned from raw data can be used as the input to a robot controller to perform photoacoustic-based visual servoing without requiring the formation of an image that is interpretable to humans.[48]

Outstanding challenges include many of the known limitations that persist across the entire field of deep learning. For example, training sets must include multiple possible variations. Generalizability across system settings and target properties (e.g., size, shape, optical absorption) is a necessity for global implementation, yet this type of generalizability is difficult to ensure for all possible cases. Network interpretability is also important to increase trust and confidence in network outputs, to understand why networks fail, and to predict network failure with minimal disruption to overall clinical workflows.

ACKNOWLEDGMENTS

This work was supported by the NIH Trailblazer Award (Grant No. R21-EB025621), the NIH Trailblazer Award Supplement (Grant No. R21-EB025621-03S), the NSF SCH Award (Grant No. NSF IIS-2014088), and the Computational Sensing and Medical Robotics Research Experience for Undergraduates Program (Grant No. NSF EEC 1852155).

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