Adaptive beamforming through model-aware intelligent agents

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Background, Motivation and Objective

Over the past years, deep learning has proven itself as a powerful tool for a variety of data processing tasks. Naturally, it has also found application in the field of ultrasound beamforming, where traditional strategies pose a tradeoff between either high framerates, e.g. *delay-and-sum* (DAS), or image quality, e.g. *minimum variance* (MV). While versatile general-purpose network structures such as stacked auto-encoders or convolutional neural networks inherited from computer vision are commonly proposed, such large networks notoriously rely on vast training data to yield robust inference under a wide range of (clinical) conditions. They moreover exhibit a large memory footprint, complicating resource-limited implementations.

Here, we propose a different approach, and leverage a model-based architecture inspired by adaptive beamforming schemes, to yield a robust and highly data-efficient adaptive beamformer able to facilitate fast high-quality imaging.

Statement of Contribution/Methods

Rather than directly predicting the beamformed signal, the proposed method utilizes a neural network that acts as an intelligent agent in parallel with the beamforming path, computing an optimal set of content-adaptive beamforming parameters in real-time.

A four-layer fully-connected network was trained to adaptively predict a set of array apodization weights based on *time-of-flight* (TOF) corrected channel data. These weights are determined such that, when applied to the TOF corrected channel data, the resulting beamformed signal matches a desired high-quality target. The latter was facilitated by using a subspace MV beamformer for offline training-data generation.

For training and testing, two separate datasets of single plane wave transmits were composed, consisting of both simulated point scatterers, as well as in-vivo data of the carotid artery and wrist acquired with a 6.25-MHz linear transducer connected to a Verasonics research platform.

Results/Discussion

Fig. 1 shows the reconstructed images of a carotid artery using three different beamforming methods. Our deep learning solution yields a high-contrast reconstruction comparable to the MV target, yet at roughly 5% of the computational cost of the MV beamformer. Furthermore, we measured an increased lateral resolution of 20.2% compared to DAS beamforming and of 10.5% compared to MV beamforming.

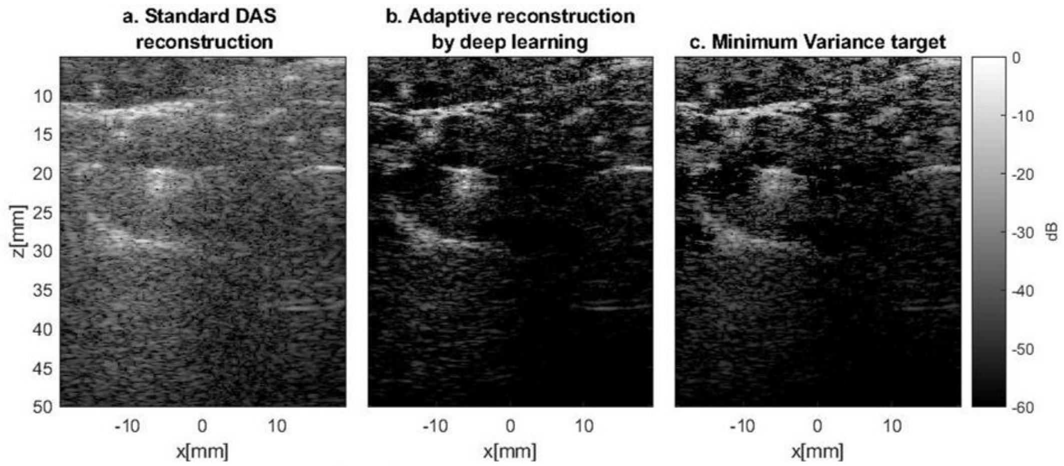

Figure 1. Plane wave acquisition of a carotid artery reconstructed using: a) Delay-and-sum (DAS) beamforming, b) Neural network based adaptive beamforming, and c) Minimum variance beamforming. Compared to DAS both adaptive methods show a reduction in clutter, resulting in a high-contrast image.