Deep-learning Image Reconstruction for Real-time Photoacoustic System

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Background, Motivation and Objective

Real-time integrated photoacoustic and ultrasound (PAUS) imaging is a promising approach to bring the molecular sensitivity of optical contrast mechanisms into practical US systems used in the clinic. One potential application is real-time blood oxygenation monitoring in the microvasculature. It requires not only multiple measurements at different optical wavelengths, but also high image quality to preserve microvascular topology. Similar to US beamformers, PA reconstruction widely uses a traditional delay-and-sum (DAS) algorithm. However, the limited view and relatively narrow bandwidth of clinical US arrays greatly degrade image quality. Here we explore PA image reconstruction based on a deep-learning technique to overcome this ill-posed problem.

Statement of Contribution/Methods

Recently, convolutional neural networks (CNNs) have been successfully applied to a variety of imaging fields. The structure can extract comprehensive features from data, replacing hand-crafted functions. Our architecture is based on U-net, where dyadic scale decomposition can access data in multi-resolution support. For training, we created synthetic data mimicking typical microvasculatures, as shown in Fig. 1 (a). The operators transforming ground-truth to RF array data are based completely on our PAUS system. We modify data into a 3-D array with two spatial dimensions and a channel dimension, where a channel packet corresponds to the propagation delay profile for one spatial point, as input to the CNN. This approach can simplify the learning process and increase accuracy.

Results/Discussion

We compared the CNN-based method with other popular reconstruction approaches including DAS, delay-multiply-and-sum (DMAS), and total-variation regularization (TV). As shown in Fig. 1 (b-e) for a particular test case, CNN provides a high-contrast image with few structural losses. Ongoing experiments are using these methods with real data recorded by our PAUS system. Obtaining real ground-truth maps is impracticable at large scale. Therefore, reducing the discrepancy between synthetic and real data is required to guarantee that a CNN learned by synthetic data works for real data. The primary drawback is non-linear scaling, which often suppresses weak signals excessively. Future work will focus on compensating for this to enable quantitative spectroscopic PAUS imaging.

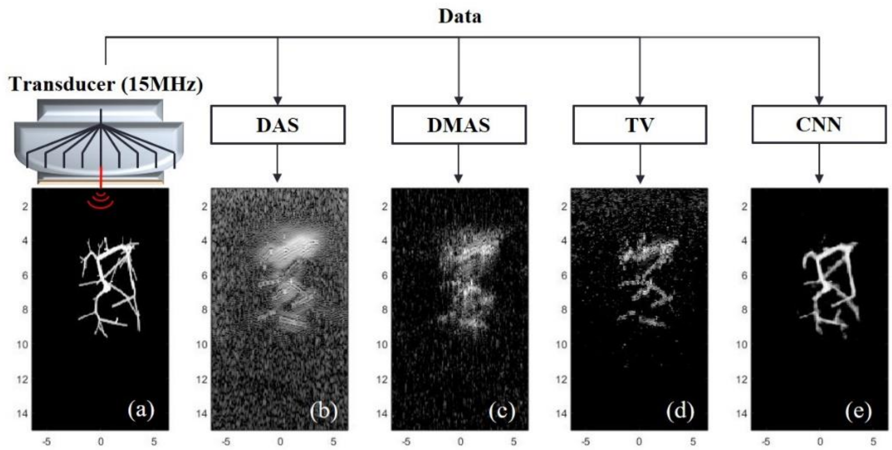

Figure 1 (a) Ground-truth image mimicking microvasculature. Synthetic data is generated by the operators based on our PAUS system (b-e) Reconstructed images from synthetic data.