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A Deep Learning Approach to Reconstruct the Photoacoustic Image Using Multi-Frequency Data

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***Abstract*—Photoacoustic imaging (PAI) is an emerging non-invasive imaging modality combining the advantages of ultrasound imaging and optical imaging. Image reconstruction is an essential topic in photoacoustic imaging, which is unfortunately an ill-posed problem due to the complex and unknown optical/acoustic parameters in tissue. Conventional algorithms used in photoacoustic imaging (e.g., delay-and-sum) provide a fast solution while many artifacts remain. Convolutional neural network (CNN) has shown state-of-the-art results in reconstruction problem. In this paper, a framework of the neural network is proposed to approach the PA imaging reconstruction using multi-frequency ultrasound sensor data. Specifically, we trained an end-to-end network to compare the performance when the transducers surround the region of interest with three different center frequencies, which receive PA signals containing different frequency spectrum information from the target. In particular, we trained and tested the network using the factitious segmented vessels' PA images from fundus oculi CT imaging after converting to PA data. From the results of the numerical simulations, the proposed frameworks have shown much better performance compared with conventional reconstruction algorithms. Moreover, the time consumption of the proposed reconstruction method outperforms other conventional reconstruction algorithms, which enables its potential to apply in real-time imaging.**

Keywords—photoacoustic tomography, reconstruction, deep learning, convolutional neural network

I. Introduction

Photoacoustic tomography (PAT) is a kind of hybrid imaging modalities that mixes both optical and ultrasonic imaging advantages. In PAT, ultrasonic wave is excited by a pulsed laser, which has embodied both optical absorption contrast and ultrasonic deep penetration [1-5]. Many practical applications have been investigated to show its great potential in both preclinical and clinical imaging, such as small animal whole body imaging and breast cancer diagnostics [6-15]. Specifically, photoacoustic computed tomography (PACT) enables real-time imaging performance, which reveals enormous potential for clinical applications. To obtain the image from the PA signals, image reconstruction algorithm plays an important role. Conventional reconstruction algorithms, e.g., filtered back-projection (FBP), are prevalent due to their fast speed. However, the imperfection of conventional algorithms is the existence of artifacts, which results in distorted images, especially in limited view configuration.

In this paper, a framework of the neural network is proposed to approach the PA imaging reconstruction using multi-frequency ultrasound sensor data. All transducers are surrounding sample with three different center frequencies: 2.25 MHz, 5 MHz and 7.5 MHz, alternately. Specifically, we trained an end-to-end network to compare the performance when the transducers surround the region of interest, which receive PA signals containing different frequency spectrum information from the target. From the results of the numerical simulations, the proposed frameworks have shown much better performance compared with conventional reconstruction algorithms. The proposed approach shows better performance on test datasets compared with U-net in this paper, which are evaluated by different indexes.

II. Method

The datasets we used to train and test the networks are generated from numerical simulation, which combines five random generated disc. Moreover, the factitious segmented vessels from fundus oculi CT imaging [16] have also been trained and tested to further validate the model. The simulation setup is that 120 transducers were placed on an annulus to acquire the PA signals from the sample, which interlace three different center frequencies: 2.25MHz, 5MHz and 7.5MHz. All simulations are implemented in k-space from the k-Wave

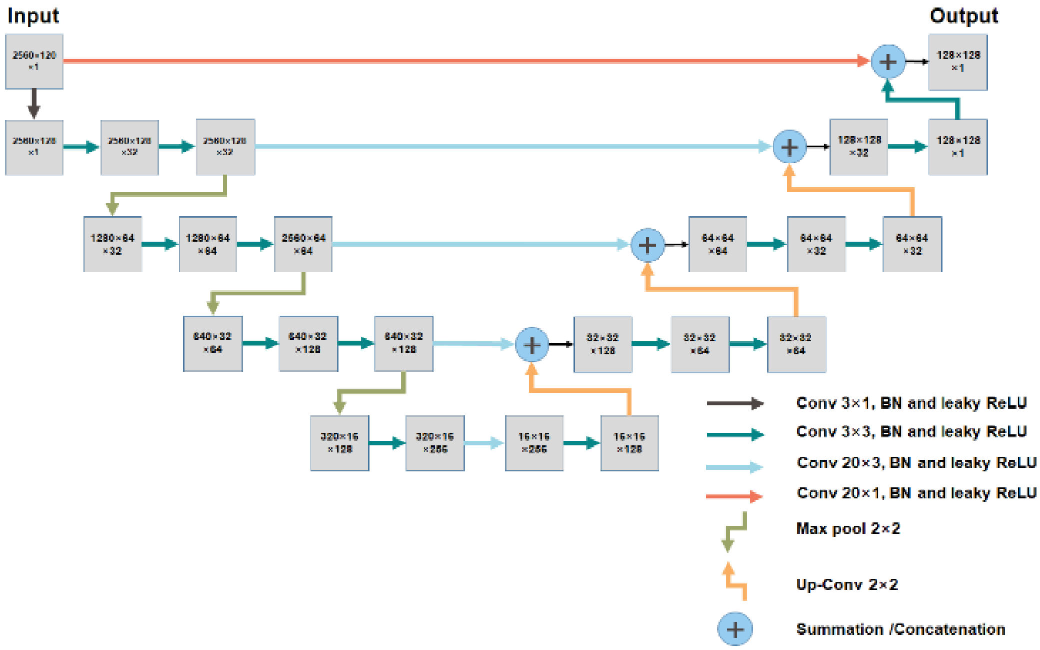

Figure 1. The architecture of ConvU-net.

toolbox of MATLAB [17], which provides raw PA data and ground truth for training.

A convolutional neural networks, ConvU-net, is implemented in this paper. The architecture of the network is modified from the U-net [18] to estimate initial pressure from raw acoustic sensor data as the Figure 1 showed. Compared with U-net, the skipped connections were modified by connecting a convolutional layer with a kernel size of (20×3) and stride of (20×1), and input image goes through a convolutional layer to align next layer.

The input of this network is the 120 channels' multi-frequencies sensor data; the time-domain information will be mapped to the spatial domain through the U-net, and generate an output image of 128×128 pixels. All networks are implemented by Pytorch, an open source deep learning library from Facebook [19]. Two networks are trained for 2000 iterations on the 4000 training datasets with numerical phantom and vessels' PA signals.

III. Results

The image reconstruction results of segmented vessels of different methods and the profile along the white dotted line are shown in Figure 2. From Figure 2, TR and DAS can reconstruct the outline of vessels with some inevitable artifacts. It can hamper the precise estimation of the pathology of vessels, because it is hard to distinguish gracile vessels and artifacts. The U-net shows a better image quality compared with TR and DAS, which has few artifacts and a visible outline. However, a small portion of the gracile vessels lacked in U-net compared with ground truth. ConvU-net recovers more information from the multi-frequency PA data and shows the best image reconstruction quality compared with TR, DAS and U-net.

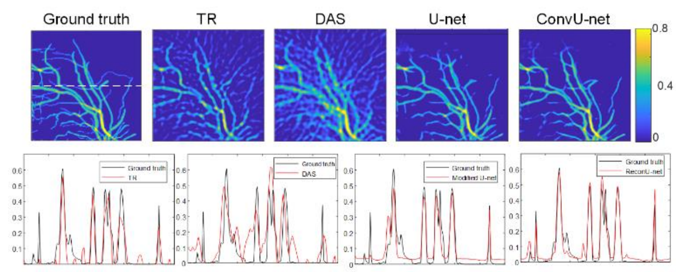

Figure 2. Top: Reconstruction results for different methods from test image of factitious segmented vessels. From left to right: ground truth, TR reconstruction, DAS reconstruction, U-net and ConvU-net reconstruction. Bottom: The profile along the white dotted line of the imaging results of Top.

Compared with ground truth, all reconstruction results have more or less deficiency of information. Quantitative evaluations of different methods are demonstrated using test sets in Table I. From Table I, we can find that DAS and TR algorithms show lower SSIM and PSNR compared with deep-learning-based methods.

TABLE I. QUANTITATIVE EVALUATION OF DIFFERENT RESULTS FOR SEGMENTED VESSELS

Algorithms	SNR	PSNR	SSIM	REL.ERROR
TR	4.356	19.093	0.208	8.293
DAS	2.293	17.030	0.141	10.338
U-net	8.725	23.462	0.428	4.643
ConvU-net	**10.701**	**25.438**	**0.611**	**3.298**

IV. Conclusion

In this paper, an image-to-image convolutional neural networks have been proposed, which directly reconstruct the PA image from the raw photoacoustic data with different center

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frequencies. We validated the feasibility of our networks on segmented fundus oculi vessels from public datasets. The proposed ConvU-net shows better performance on test datasets compared with conventional methods and other deep learning method, which are evaluated by different indexes. The ConvU-net exhibits a huge potential to reconstruct complex vessel in preclinical and clinical *in vivo* PA imaging combined with multi-frequencies transducer array. In the future work, we will further push *in vivo* validation of the proposed network. Furthermore, the resolution may be also improved by increasing the depth of ConvU-net, which will be done in the future.

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