Application of Image Restoration in PA Signal Denoising

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***Abstract*—Reducing the noise in sensor data is an important problem, and acoustic aberration correction is an instance in photoacoustic tomography (PAT). Inspired by the excellent performance of deep learning in many problems of signal processing, we use a framework called DuRN from the image restoration problem to be applied to the acoustic aberration correction. After experiments, it has been proved that our approach has achieved good results.**

I. Introduction

IN modern society, various sensors are widely used. Analog circuits then amplify and process the signals from these sensors. In many tasks, due to objective limitations, weak signals are often accompanied by noise that degenerates the quality of signals. To this end, we need to reconstruct the target signal from the signal with noise.

Acoustic aberration correction is an example of signal denoising tasks. It is applied to the photoacoustic (PA) [1] sinogram before PA image reconstruction. There are multiple methods to undertake it, such as using simple mathematical transformations for signal post-processing. Compared to those method with fixed parameters, deep learning has powerful advantages. With learnable parameters, depth neural network (DNN) has achieved great success in a large number of fields including signal processing. With learnable parameters, depth neural network has achieved great success in a large number of fields, and it is no exception in signal processing D. Yu [2], such as digital signal processing Shevitski B [3], time-domain signal reconstruction Y. Wang [4], and EEG signal classification with LSTM S Hochreiter [5], Nagabushanam P [6].

Due to the outstanding performance of deep learning on a variety of tasks, we found a way to apply its method to acoustic aberration correction here — **Image Restoration**, which is a typical task in computer vision, has a highly matched scenario as acoustic aberration correction do. It is the operation of taking a corrupt/noisy image and estimating the clean, original image, and it's just like noise removal from the PA sensor data by thinking of it as an image. Compared with the previous work Lyu T [7] using U-Net Ronneberger O [8], the image restoration algorithm we choose is more suitable for the specific task here than the semantic segmentation algorithm. Considering the time and computational resource cost, we use a nice framework — **Dual Residual Networks** (DuRN) Liu X [9] as our model.

Our main contribution is to find the wide application prospect of the algorithm of image restoration in signal denoising.

II. Dataset

We are given eight paired human brain photoacoustic sinogram. Each pair of sinogram consists of the sinogram with noise and the corrected sinogram as ground truth. Among them, each sinogram contains 256 channels of signals, and the signals of each channel provide 1200 data points. The value range of data points is about -0.2 to 0.2.

Taking the seventh group of data as an example (in order to be consistent with the later machine learning results), the noise of 256 channels is visualized after fast Fourier change. As is shown in Fig.1 ,we can see that the noise is mostly concentrated in low frequency and high frequency, because the signal itself is also concentrated in low frequency and high frequency.

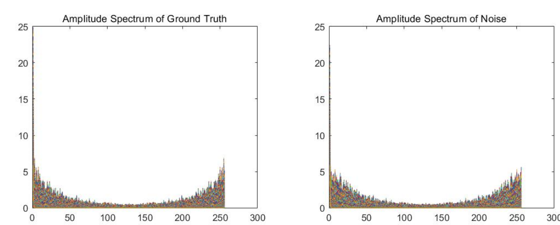

Fig. 1. amplitude spectrum of the seventh group

Moreover, when we take the noise of the 1^{st} to the 4^{th} channels for special case analysis, we can know from Fig.2 that the noise of a specific channel is chaotic and irregular.

Macroscopically, comparing the noisy signal with the ground truth, it can be seen from Fig.3 that the larger data points become larger under the influence of noise, and the gap between the smaller data points and adjacent data points decreases under the influence of noise.

In addition, each channel of noisy signal actually has only 945 data points, which is missing the last 255 data points compared with ground truth.

III. Insights

We found that there is a strong correlation between the 256 channels in the PA sensor data, which is similar to the semantic information between pixels in an image. It is the basic motivation for us to use image restoration algorithms

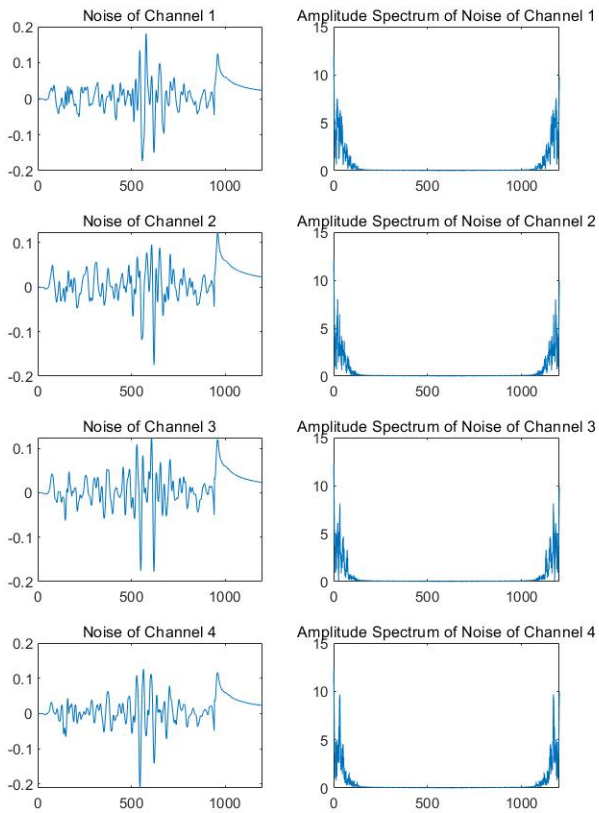

Fig. 2. amplitude spectrum of noise of channel 1-4 of the seventh group

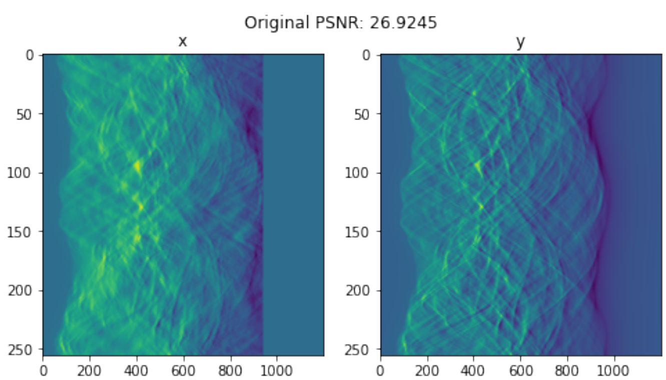

Fig. 3. The seventh set of data

here.

In the task of computer vision, we usually treat the image data as a two-dimensional whole, rather than cutting each pixel or line and then processing it separately. Therefore, we speculate that it may be feasible to regard this signal data as an image, 256 channels as one of the dimensions of the two-dimensional image, and then apply image restoration algorithms to this problem.

IV. Baseline Methods

We tried the following methods as experiments and comparisons.

A. Average filtering

Average (or mean) filtering is a method of ‘smoothing’ images by reducing the amount of intensity variation between neighbouring pixels. The average filter works by moving through the image pixel by pixel, replacing each value with the average value of neighbouring pixels, including itself.

B. Gaussian filtering

Gaussian filtering is a linear smoothing filtering, that is, the process of weighted average of the whole image. The value of each pixel is obtained by weighted average of itself and other pixel values in the neighborhood. This weight is given by Gaussian function because it regards the noise distribution as normal distribution. Under this premise, Gaussian filtering will have better performance.

C. Minus the Mean of Noise(MMN)

Simulating the conditions of machine learning, we take the first six pairs of PA signals as known conditions, and obtain the average value of noise as the embodiment of noise law. Thus, substracting the average value of noise from the signal with noise is used as the algorithm of signal processing.

V. Dual Residual Networks

Follow the original paper of DuRN Liu X [9], we figured out its main idea and basic framework. The main innovation of DuRN lies in the application of residual networks He K [10]. It makes changes in the organizational form of the original residual block to increase the interactivity and flexibility between modules, which is illustrated in Fig. 4 of the original paper.

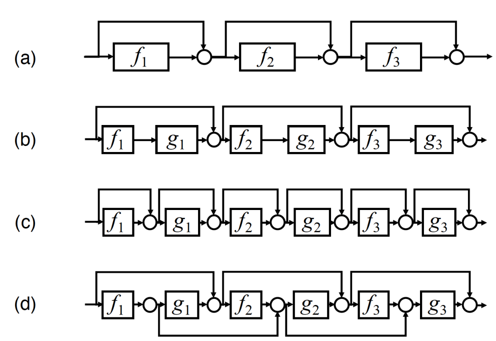

Fig. 4. Different construction of residual networks with a single or double basic modules. The proposed ”dual residual connection“ is (d).

The residual block plays two important roles in this kind of problem. The first is to make the original input information more easily retained in the output, because whether in the task of signal denoising or image restoration, the similarity between input and output is very high, so we do not want the algorithm to make significant changes to the input. The second is to make our model easy to train.

In Liu X [9], researchers carried out experiments on some image restoration datasets, including Gaussian noise removal, motion blur removal, haze removal, raindrop detection and removal, and rain-streak removal as Fig. 5 of the original paper. We can visually see how these datasets have in common with our tasks.

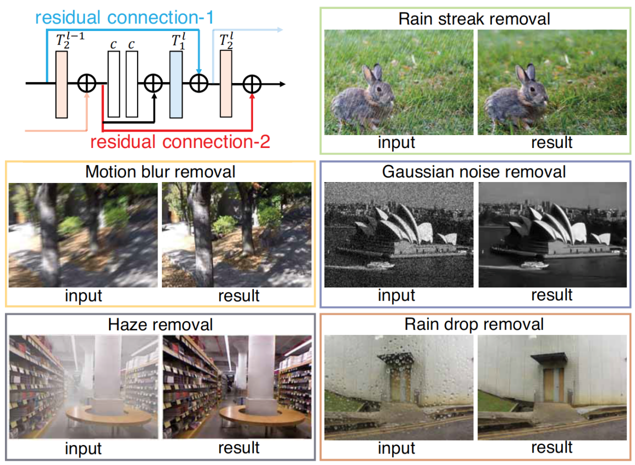

Fig. 5. Upper-left: the structure of a unit block having the proposed dual residual connections; T_1^l and T_2^l are the containers for two paired operations; c denotes a convolutional layer. Other panels: five image restoration tasks considered in this paper.

It provides four implementations of the Dual Residual Block (DuRB) it used for different types of problems, as illustrated in Fig. 6 of the original paper. Here we the lightest DuRB-P and remove its batch normalization Ioffe S [11] since our dataset is small and the solution of our problem is likely to be trivial.

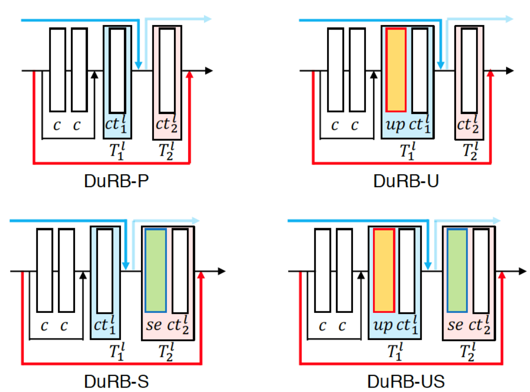

Fig. 6. Four different implementations of the DuRB; c is a convolutional layer with 3×3 kernels; ct_1^l and ct_2^l are convolutional layers, each with kernels of a specified size and dilation rate; up is up-sampling (we implemented it using PixelShuffle); se is SE-ResNet Module that is in fact a channel-wise attention mechanism.

We got pretty good outputs using this framework.

VI. Experiments

A. Traditional Signal Processing Denoising Methods

Firstly, we can see that the traditional signal processing denoising method has poor effect, whether intuitively or numerically. The reason is that the denoising method of signal processing is limited to the type of noise. Mean filtering is suitable for smooth changing images with abrupt noise, and Gaussian filtering is suitable for Gaussian noise satisfying normal distribution. In PA signals, the data changes dramatically, and the noise has no law to follow. Therefore, these two methods only blur the image, and even amplify the noise near the larger value. Through such bluring processing, PSNR and SSIM are improved by a small amount.

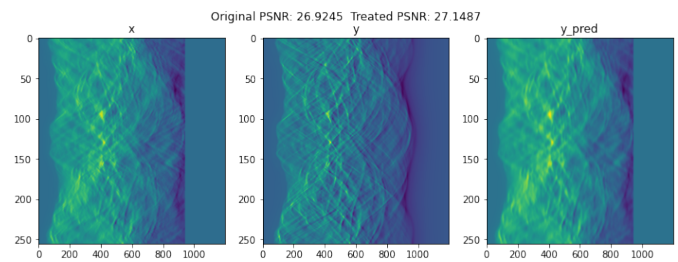

Fig. 7. Results of mean filtering of the seventh group of PA signals

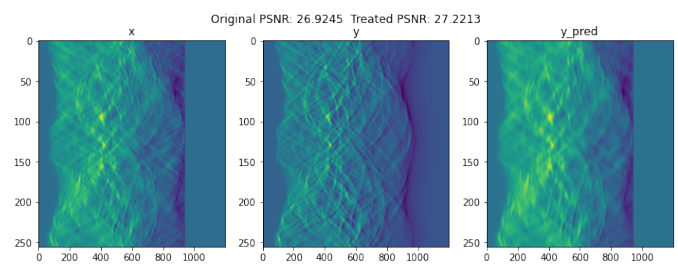

Fig. 8. Results of Gaussian filtering of the seventh group of PA signals

B. MMN

MMN has achieved certain results. It is inferred that the reason is that the given data set is also manually generated, and the noise generated in this way has a certain law between different groups. However, in the actual situation, it is not difficult for us to imagine that the thickness of human skull and its influence on ultrasound are also regular in the same position of different people. It is the existence of this potential law that proves the feasibility of neural network, because neural network can certainly find this law through a lot of learning and operation.

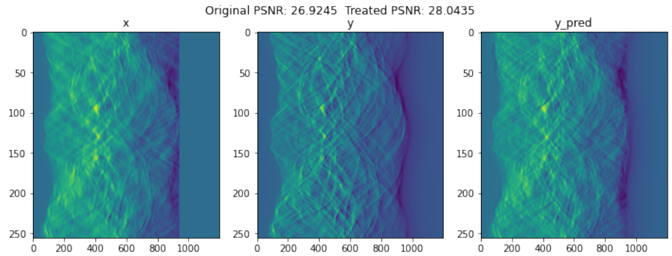

Fig. 9. Results of MMN of the seventh group of PA signals

TABLE I
COMPARISON OF DENOISING METHODS

Method		Test Time(s)	Evaluation Indicator	
			PSNR	**SSIM**
Median blur	3*3	0.5	27.037	0.594
	5*5	0.5	27.149	0.599
	7*7	0.5	27.240	0.603
Gaussian blur	3*3	0.8	27.015	0.592
	5*5	0.5	27.068	0.595
	7*7	0.4	27.134	0.598
	9*9	0.4	27.179	0.600
	11*11	0.5	27.221	0.602
MMN		0.8	28.043	0.743
DuRN(ours)		4.8	**30.334**	**0.809**

C. DuRN

We use the data of index from 1 to 6 as the training set, and uses the data 7 and data 8 to perform evaluation.

We use Adam optimizer Kingma D P [12] with the learning rate of 5e-5 and train the DuRN for 100 epochs with 1 GeForce GTX 1080.

The best effect of DuRN is to clarify the rapidly changing edge of the signal, restore the larger signal value, and try to reconstruct the last 255 data points where the noisy signal is missing. This effect is completely impossible to achieve by the above methods.

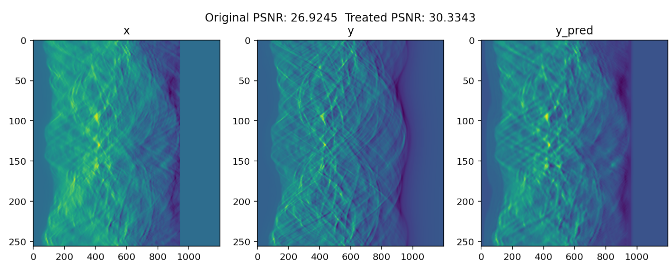

Fig. 10. Results of DuRN of the seventh group of PA signals

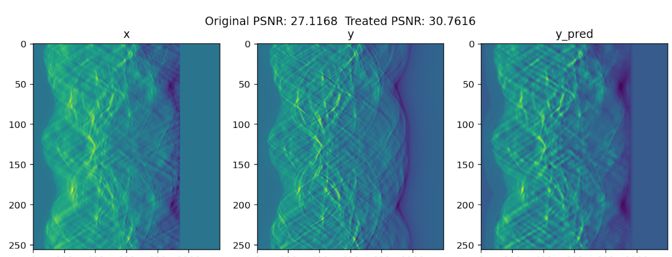

Fig. 11. Results of DuRN of the eighth group of PA signals

D. Comparison

We summarize the outputs of all methods and get Table 1, from which we can see that DuRN achieves the optimal value on both evaluation indicators on the basis of consuming a certain time cost.

VII. CONCLUSION

We have found that image restoration algorithms such as DuRN can be successfully used in acoustic aberration correction and it shows excellent performance compared with previous methods. We can also explore the related problems further from some directions in the future, for example: Can we find a better image restoration architecture to make it more targeted for the task of signal denoising? Is there any more application prospect of deep learning method in signal processing? We will continue to verify these issues.

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