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Stochastic noise suppression method for seismic data based on multi-scale and dense residual network

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ABSTRACT: Random noise suppression is an important step to improve the signal-to-noise ratio of seismic data. The quality of the denoising results will directly affect the results of subsequent seismic treatment. With the development of deep learning, the method based on deep learning has been successfully applied to the random noise attenuation of seismic data. In view of the limitations of convolutional neural networks in feature extraction, this paper proposes a deep convolutional network structure combining multi-scale and dense residual blocks (DFF-ADNet), and introduces an attention mechanism into the network, which not only emphasizes the key features, but also efficiently extracts the noise information hidden in the complex background. The network is trained on synthetic seismic data, and the trained network is directly used for testing synthetic seismic data and complex raw seismic data with unknown noise levels. Experiments compare several classical denoising algorithms, and the results show that DFF-ADNet has a good random noise suppression effect, which is superior to the comparison methods in processing detailed information and texture information, and has minimal damage to useful seismic signals.

KEYWORDS: random noise attenuation, multi-scale, attention mechanisms, Convolutional neural networks

I. INTRODUCTION

In the field of seismic exploration, the influence of instruments, environment and other factors makes it inevitable to introduce random noise in the process of seismic data acquisition, and the existence of random noise reduces the signal-to-noise ratio of seismic signals, and the seismic signals with low signal-to-noise ratio will affect the subsequent seismic data processing. Therefore, the attenuation of random noise in seismic data has become one of the core problems in seismic data processing, and the elimination of random noise and the retention of effective information are the key points of seismic data processing[1].

At present, researchers have proposed many effective methods for suppressing random noise, and the seismic noise suppression methods can be divided into four categories: methods based on predictive filtering [2], methods based on transformation, methods based on matrix ranking, and methods based on deep learning. Although the above-mentioned denoising methods have achieved good results in noise suppression, with the continuous improvement of seismic exploration requirements, the traditional denoising methods not only require a large time cost in the face of massive seismic data, but also are difficult to ensure that the effective signal is not removed while denoising. Therefore, it is necessary to introduce new methods from other fields to noise suppression of seismic data.

With the rapid development of the field of deep learning, deep learning technology has been applied to the field of seismic exploration. Convolutional neural networks (CNNs) are increasingly widely used in feature learning, object detection, semantic segmentation, and other fields[3]. Convolutional neural networks have also developed rapidly in the field of image denoising, and some CNN-based denoising methods have been proven to be effective in suppressing certain types of seismic noise. In order to improve the signal-to-noise ratio of complex seismic signals, this paper proposes a Seismic Data Noise Suppression Network Based on the Combination of Multi-scale and Dense Residual Blocks (DFF-ADNet). DFF-ADNet is mainly constructed by three dense multi-scale convolutional feature fusion blocks (DFF)[4] and attention modules[5]. Among them, dense blocks can strengthen the transmission of local feature information and increase the ability to capture signal details, multi-scale convolution uses filters of different sizes to extract features of different granularities, and uses feature fusion structure to fuse the extracted features, which can obtain a larger range of receptive fields, so as to better capture the context information. The attention module helps the network extract noise from complex backgrounds.

II. METHOD

In seismic data processing, raw seismic data can be seen as the sum of clean seismic signals and noise[6]. Assuming x is a clean signal and n is random noise, the input data can be expressed as:

$$y = x + n \qquad (1)$$

where y represents noisy seismic data. Seismic data denoising is the distribution of clean data x that learns from the noise data y, which can be expressed as:

$$x \approx \hat{x} = Net(x+n) \qquad (2)$$

where Net( ) is the trained network, and then compares the difference between the clean data (labels) and the output of the network, so that continuously converges to x by minimizing the loss function value. We use the mean square error function (MSE) as the loss function. The formula is as follows:

$$L_{MSE} = \frac{1}{2N}\sum_{i=1}^{N}\|\hat{x} - x\|_F^2 \qquad (3)$$

where N is the amount of input data and ‖‖F is the F-norm.

III. DENOISING NETWORK

The DFF-ADNet model is shown in Figure 1. In this paper, we are mainly looking at grayscale seismic profile denoising, which means that the input channel of the head is 1. The first layer of the network consists of a multi-core convolutional layer and a LeakyReLU activation function, which is used to convert the input single-channel portion to a multi-channel part. For the convolutional layer, the kernel size is set to 3 and the number of cores is 32. The middle part is the main part of the model and uses a multi-scale feature fusion (DFF) block to achieve denoising. As shown in Figure 2, several CNNs with kernel sizes of 3, 5, and 7 were selected in the DFF block to extract potential features with different particle sizes. For each kernel size, we designed a dense structure consisting of three Cov+BN+LeakyReLU, with a kernel count of 32 for each convolutional layer, and then stitched the three outputs by cat. Then, a Cov+BN+LeakyReLU structure is adopted, in which the convolutional layer kernel number is 32, and the connected tensor with 32 × 3 channels is fused into a 32-channel tensor. In this way, the output size of the DFF block is the same as the input size. Then, the residual structure is used to obtain the residuals of the input of the DFF block and the output of the fusion block. In the dotted box in Figure 1, FEB uses cascading operations to fuse the noisy seismic data with the output feature map of the DFF layer to enhance the feature representation ability of the network, and Tanh can convert the obtained features into nonlinear features and normalize them. The AE in the dotted box is an attention module, which is used to enhance the ability of the network to extract noise, which mainly consists of two steps: the first step is to convert the number of channels to 1 by using 1×1 convolution to perform feature compression; The second step multiplies the obtained results by the output of the convolutional layer in the FEB module to extract a more significant noise signature. Finally, the residual learning is used to subtract the extracted noise from the input noisy seismic data to obtain the denoised seismic data.

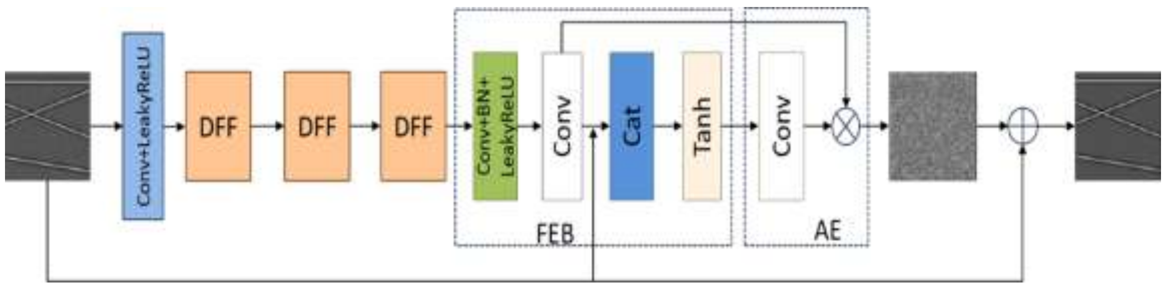

Fig.1 Residual Attention Module

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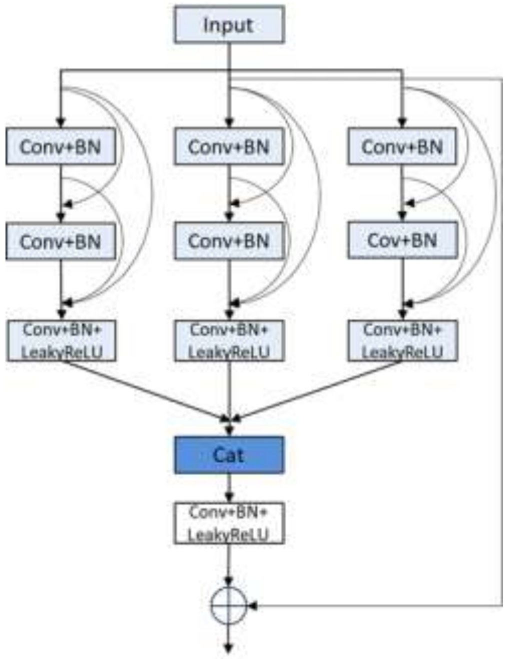

Fig. 2. Multi-scale dense residual module(DFF)

In a traditional CNN, the input of each layer comes only from the output of the previous layers, whereas in a dense block, the input of each layer comes not only from the previous layer, but also from the output of all previous layers in that block. The design of such dense connections can deepen the depth of the network and enhance the feature extraction ability of the network [19]. In addition, as the number of network layers increases, the detail information of the image may be lost. Multi-scale feature fusion can reduce the loss of information by retaining feature information at different scales[20]. In this paper, several CNNs with kernel sizes of 3, 5, and 7 are combined with dense residual blocks to form a Multi-scale dense residual module(DFF).

IV. EXPERIMENT

A. Data Generation and Experiment Arrangement

The denoising method of deep convolutional neural networks requires a large number of training samples to train the model. In this paper, three public synthetic seismic data (1997 BP 2.5-D dataset, 2007 BP TTI velocity analysis, and Bpvelanal 2004 test dataset) were selected as training sets. Since the seismic data in different windows contain different details, the data was intercepted using a sliding window with a block size of 128×128 steps of 40, and the data was enhanced by rotation and flipping operations, and then normalized, while noise of different signal-to-noise ratio levels was randomly added to obtain a training set of 23,444 pairs.

The training of the whole network is carried out in Python 3.7, CUDA12.2, Pytorch2.0.1 deep learning framework, and the Adam optimizer is adopted. The batch size is set to 10, the number of iterations is 50, and the learning rate changes from 1e-3 (1~20), 1e-4 (20~40), and 1e-5 (40~50) during the training process. Save the trained network model and test the seismic data with different noise intensities. For the network model test, 80 synthetic test samples and one actual seismic sample were selected, with a sample size of 128×128.The configuration of the computers used was as follows: CPUIntel i5-12400F, Windows 10 64-bit operating system, 16 GB RAM and NVIDIA GeForce RTX 2060s.

B. Data Analysis

The DFF-ADNet proposed in this paper is applied to the simulated seismic data and actual seismic data, and compared with the FX domain deconvolution, UNet method and DnCNN method. The signal-to-noise ratio (SNR) and structural similarity (SSIM) were used to evaluate the denoising effect of different methods. SNR is defined as

$$SNR = 10lg\frac{\|x\|_F^2}{\|x-\hat{x}\|_F^2} \tag{4}$$

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Where is clean seismic data, is the denoised seismic data. SSIM is defined as

$$SSIM(x,\hat{x}) = \frac{(2u_x u_{\hat{x}}+c_1)(2\sigma_{x\hat{x}}+c_2)}{(u_x^2+u_{\hat{x}}^2+c_2)(\sigma_x^2+\sigma_{\hat{x}}^2+c_2)} \tag{5}$$

where and are the mean of and , respectively, and are the corresponding variances, respectively, is the covariance of and , and are constant values used to maintain stability.

C. Synthetic Seismic Data

In order to verify the superiority of the DFF-ADNet network, Fig. 3 shows the synthetic seismic data in the test set and the denoising results obtained by different methods. Fig. 3a shows the noise-free synthetic seismic data; Fig. 3b shows the seismic data obtained by adding Gaussian noise with a noise level of 8 to Fig. 3a, with an SSIM of 0.7815; Fig. 3c to Fig. 4f are the denoising results obtained by the f-x prediction filtering, U-Net and DnCNN methods, respectively, and Fig. 3f is the denoising results obtained by the proposed method. The SNR and SSIM are shown in Table 1, and it can be seen that the SNR and SSIM of the noise suppression results of the proposed method are better than those of other methods. Observing Fig. 3c, it can be found that after using the f-x domain prediction filter to denoise, although some of the random noise is suppressed, there are still many clearly visible random noise in the seismic data. The seismic data in Fig. 3d and Fig. 3e are blurry and unclear at the edges to varying degrees. The seismic data in Fig. 3f is of the highest quality, which illustrates the effectiveness of DFF-ADNet in noise removal. In order to analyze the denoising results more intuitively, Fig. 4 shows the residual profiles after denoising by different methods. There are many remnants of seismic data from Fig. 4a to Fig. 4c, and the noise suppression effect is poor. There are few residual seismic data in Figure 4d, which indicates that DFF-ADNet has better noise suppression and local detail retention capabilities.

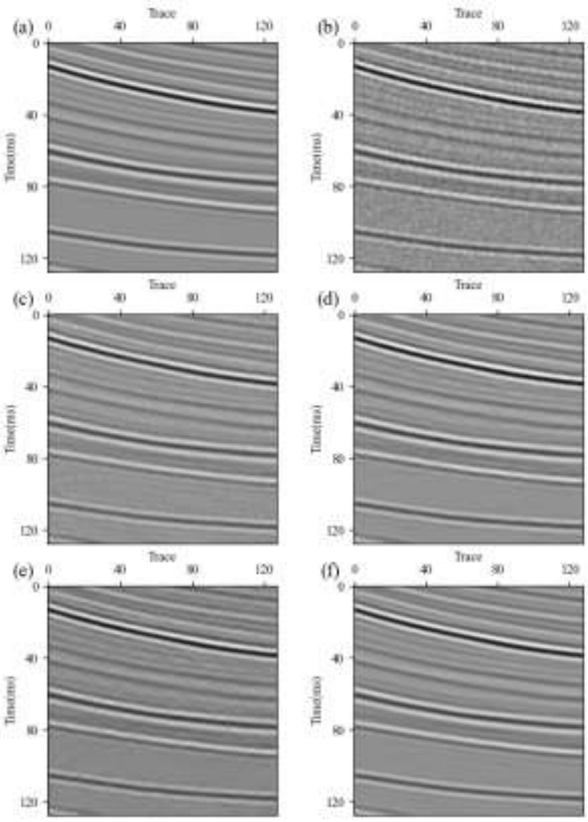

Fig. 3. Denoising results of synthetic seismic data. (a) Synthetic clean data. (b) Noisydata. (c) f-x. (d) U-Net. (e) DnCNN. (f) DFF-ADNet

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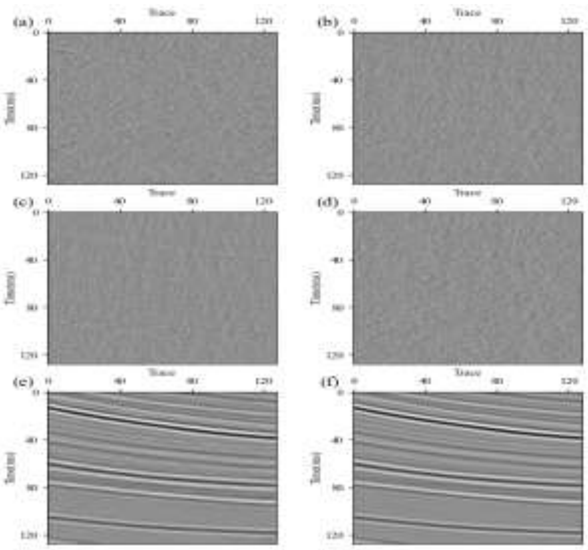

Fig. 4. Residual profiles obtained by different denoising methods for synthesizing seismic data. (a) f-x. (b) U-Net. (c) DnCNN. (d) DFF-ADNet

Fig. 5 shows the f−k spectra of the synthesized data and the results of the four denoising methods. As can be seen, there is a lot of noise in Fig. 5c, and there are some remnants of noise in Fig. 5d and Fig. 5e in the effective band of the f−k spectrum from 20 to 80 Hz. The f-k spectrum of our method is closest to the f-k spectrum of the original signal and has the best effect on noise removal.

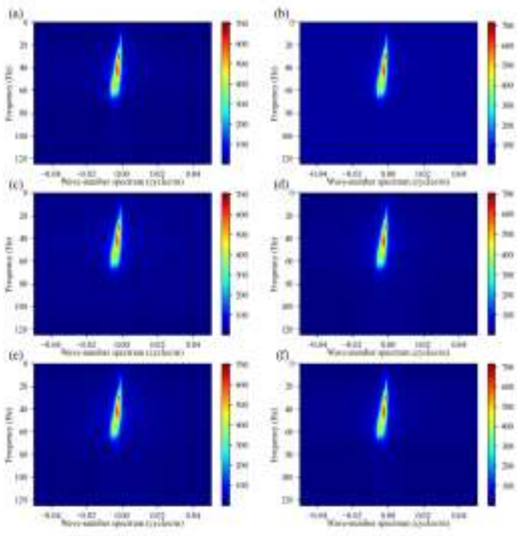

Fig. 5. The f − k spectrum on the synthetic data. (a) Synthetic clean data. (b) Noisydata. (c) f-x. (d) U-Net. (e) DnCNN. (f) DFF-ADNet

D. Real Seismic Data

In order to verify the practicability of DFF-ADNet, we applied DFF-ADNet to field seismic profiles and compared it with other denoising methods. The site seismic profile is zoomed to 0–255, as shown in Figure 6. Due to the interference of random noise, the in-phase axis of the original tract set is not clear, and the effective signal with weak energy is difficult to identify. Fig. 6 shows the denoising results of the above four methods, and Fig. 7 shows the corresponding residual profiles.

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It can be seen that the denoising results of the f-x deconvolution method still contain a lot of noise, the noise suppression is not obvious, and a lot of effective information is lost (Fig. 6b, Fig. 7a). The UNet convolutional neural network suppresses random noise better than traditional methods, but impairs the effective signal to a certain extent (Fig. 6c, Fig. 7b). After the noise suppression by the DnCNN method, the random noise is effectively removed and the effective signal is more fully retained, but it can be observed from the denoising results and residual profiles that the weak effective signal in the red box is suppressed together with the random noise (Fig. 6d and Fig. 7c). In this method, the random noise is removed more thoroughly, the texture details are also protected, and the residual tract set is less valid, which is conducive to the protection of weak signals (Fig. 6e, Fig. 7d).

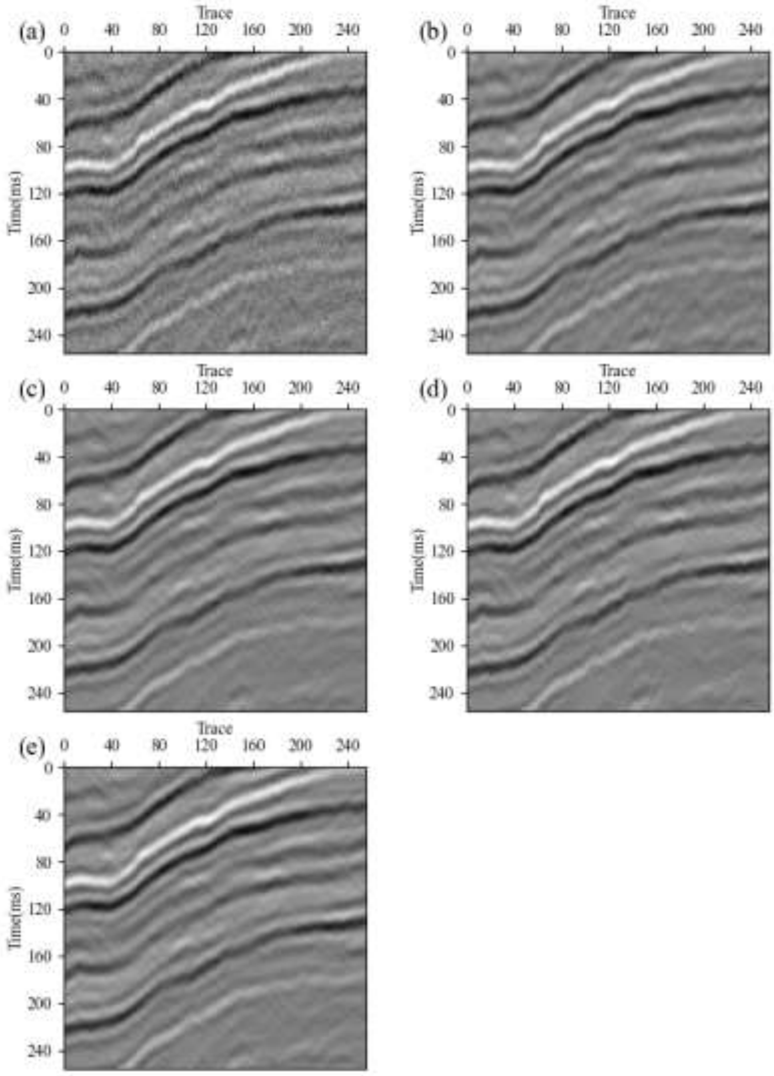

Fig. 6. Denoising results of real seismic data. (a) Synthetic clean data. (b) Noisydata. (c) f-x. (d) U-Net. (e) DnCNN. (f) DFF-ADNet

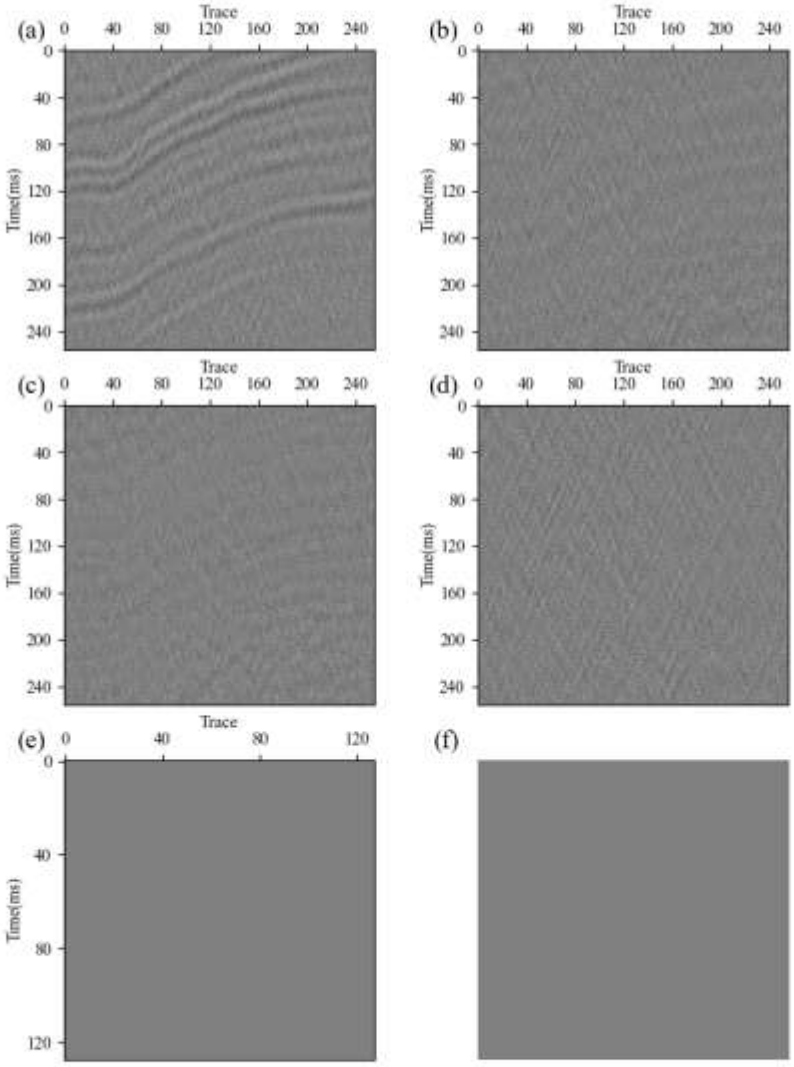

Fig. 7. Denoising results of real seismic data. (a) Synthetic clean data. (b) Noisydata. (c) f-x. (d) U-Net. (e) DnCNN. (f) DFF-ADNet

V. CONCLUSION

In this paper, we propose a convolutional neural network combining multi-scale and dense residuals for random noise suppression of seismic data. In this paper, DFF proposes to use filters with different convolutional kernels to extract features from different granularities in parallel, so as to obtain richer information, and combines the advantages of residual learning to cite a dense residual structure to retain richer details while removing noise. In addition, the model introduces an attention mechanism (AE) to better retain detailed information. At the same time, in order to better learn the characteristics of the negative area of seismic data, the LeakyRelu activation function is used to make the network fit the data better. The processing results of synthetic seismic data and actual seismic data show that the convolutional neural network method combining multi-scale and dense residuals proposed in this paper can suppress the random noise more thoroughly and retain more detailed information.

REFERENCES

[1]. Liu, H., Li, Z., Lin, S., & Cheng, L. (2023). A Residual UNet Denoising Network Based on Multi-Scale Feature Extraction and Attention-Guided Filter. Sensors, 23(16), 7044.

[2]. Wang, H., Chen, W., Huang, W., Zu, S., Liu, X., Yang, L., & Chen, Y. (2021). Nonstationary predictive filtering for seismic random noise suppression—A tutorial. Geophysics, 86(3), W21-W30.

[3]. LI, X. Y., KONG, X. Q., & HOU, X. H. (2012). High frequency noise suppression by empirical mode decomposition in the frequency-spatial domain based on high-pass filter. Progress in Geophysics, 27(3), 1070-1077.
[4]. Multiscale spatial attention network for seismic data denoising. IEEE Transactions on Geoscience and Remote Sensing, 60, 1-17.
[5]. Tian, C., Xu, Y., Li, Z., Zuo, W., Fei, L., & Liu, H. (2020). Attention-guided CNN for image denoising. Neural Networks, 124, 117-129.
[6]. Zhang, K., Zuo, W., Chen, Y., Meng, D., & Zhang, L. (2017). Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. IEEE transactions on image processing, 26(7), 3142-3155.