

MEU Convolutional Neural Network and Random Noise Suppression of Seismic Data

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Abstract. In allusion to the strong interference problem of random noise in seismic exploration, this paper proposed a Multiscale enhancement U-Net (MEU-Net) for the first time. First, the network carries out multiple convolution and pooling on the data in the backbone feature extraction network, then conducts channel addition, convolution and upsampling in the enhancement feature extraction network for extracting and restoring data information, finally, further improve the denoising effect through the dilated convolution, residual module and attention mechanism in the multi-scale enhancement module. The actual data application shows that the method in this paper can achieve good denoising effect under noise with different intensities, and can be widely used in data denoising processing.

Keywords: Multi-scale enhancement, Denoising, Convolutional neural network.

1. Introduction

The random noise of seismic data brings adverse effects on subsequent data processing and interpretation. Random noise suppression is the basic work of seismic data processing, which aims to improve the signal-to-noise ratio of seismic data, thereby improving the efficiency and accuracy of subsequent seismic data processing and interpretation.

In recent years, many scholars have proposed many methods for random noise suppression. At present, the denoising methods of seismic data are mainly composed of methods based on model and methods based on data drive. Among them, the methods based on model include: K-L transform filtering [1], F-X filtering [2], Radon transform [3] and other methods. The methods based on data drive are mainly the application of deep learning technology. CNN uses its unique convolution structure, which has a significant effect in the field of seismic data denoising [4] [5]. Liu et al. [6] proposed multi-level wavelet convolutional neural network (MWCNN) model proposed, considered the wavelet domain distribution characteristics of the image, proposed a multi-level wavelet CNN framework, combined discrete wavelet transform with convolutional network, fully considered the frequency domain features of the image. Ma used DnCNN [7] for seismic data denoising, used residual learning and batch normalization accelerate the training process while improving denoising performance. High-quality denoising results are achieved without the need to model the data and manually select parameters.

We add the multi-scale enhancement module in the structure of the U-Net network and propose the MEU-Net network for the first time. First, we add random noise to the public Hokkaido F3 data, obtain noisy data and generate training set; then train the data through MEU-Net, moreover, adjust the hyperparameters of network through the loss change during the network iteration process, so that the network reaches the best condition. Finally, median filtering, CNN and U-net are compared to show the effectiveness of method in this paper.

2. Method

2.1 Problem Definition

If the seismic data contains random noise, the seismic data can be represented as

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

In the formula: x is the effective signal; y is the seismic record with noise; n is the added Gaussian noise;

The basic idea of deep learning is to build the mapping relationship between x and y through the following formula:

$$\hat{x} = Net(y; \{W, b\}) \quad (2)$$

In the formula: Net is the deep learning network; $\hat{x}$ and y are the denoising result obtained by the network prediction; $\{W, b\}$ is the network parameter, W is the weight, and b is the bias.

2.2 CNN Architecture

MEU-Net is mainly composed of the backbone feature extraction module, the enhancement feature extraction module and the multi-scale enhancement module, its structure is shown in Fig.1:

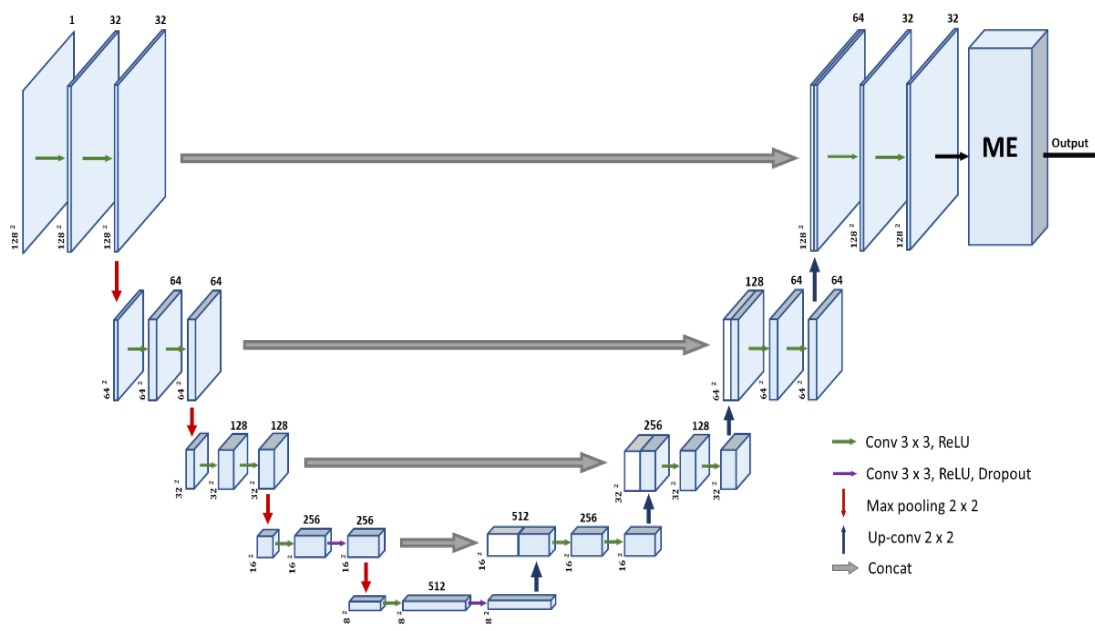


Fig. 1 MEU-net framework

The encoding process is composed of 5 groups of backbone feature extraction modules, each group of backbone feature extraction modules is composed of 3 convolutional layers, and there is a pooling layer between each group of backbone feature extraction modules. The 128×128-dimensional input data is encoded as 8×8-dimensional feature information, the convolution kernel size is set to 3×3, and the step is set to 1. The pooling layer with step 2 achieves the effect of downsampling, so that the network obtains different perceptual horizons. After each main feature extraction module and pooling operation, the size of the feature map is compressed to 1/2 of the last operation, the number of channels of the corresponding feature map is 2 times that of the last feature extraction module operation, it ensures that feature information is not lost. Correspondingly, the decoding process is composed of 5 groups of enhancement feature extraction modules, each group of enhancement feature extraction is composed of 3 convolution layers, and upsampling is carried out between each group of enhancement feature extractions. After each upsampling, the length and width of the feature map become double the original, the number of channels becomes 1/2 of the original, which realize the structural symmetry of the encoding and decoding processes. We added two jumpers between the corresponding layers of encoding and decoding, it makes the network to efficiently fuse features of different scales. Finally, the network denoising effect is further optimized through the multi-scale enhancement module (as shown in Fig.2).

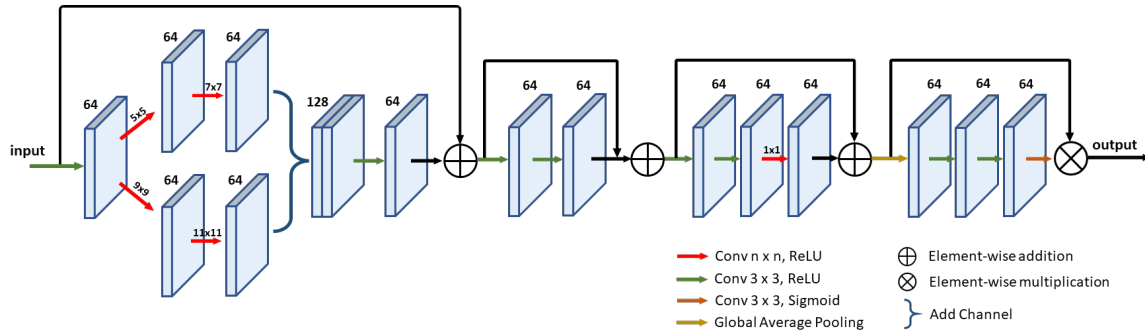


Fig. 2 multi-scale enhancement module

In the multi-scale enhancement module, first, we carry out multi-scale dilation convolution on the input data, and introduce residual units in each convolution module to avoid gradient explosion and gradient disappearance. Finally, the attention mechanism is used to obtain different weights for each channel.

The attention mechanism allows the network to recalibrate features by learning global information and builds the interdependence among feature channel. First, the global average pooling is carried out on the input feature map to obtain the feature map with size of $C \times 1 \times 1$ (C is the number of feature map channels). The process is as follows:

$$Z_c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W u_c(i, j) \quad (3)$$

Then the feature map is activated by the Sigmoid function to obtain the weight of each channel, the process is as follows:

$$S = \sigma(g(z, W)) = \sigma(W_2 \times \text{ReLU}(W_1 z)) \quad (4)$$

And

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (5)$$

In the formula: $W_1 \in R^{C \times C}$, $W_2 \in R^{C \times C}$.

Finally, the weights are reassigned to each channel, the process is as follows:

$$\tilde{X}_C = F_{scale}(u_c, s_c) = s_c \times u_c \quad (6)$$

In the formula: $\tilde{X} = \{\tilde{X}_1, \tilde{X}_2, \dots, \tilde{X}_C\}$, $u_c \in R^{H \times W}$.

Since random noise is widely distributed in the whole seismic data, we need to calculate the loss of the prediction result of each pixel point. The process is as follows:

$$loss' = \sum_{i=0}^n \sum_{j=0}^m (x[i, j] - \hat{x}[i, j])^2 \quad (7)$$

And

$$loss = \frac{1}{n} \sum_{k=0}^{k=N} loss'_k \quad (8)$$

In the formula: n is the time sampling interval of the seismic data; m is the trace number of the seismic data; x is the original noise-free seismic data; $\hat{x}$ is the denoised output of the noisy seismic data; $loss'$ is the sum of individual data errors; $loss$ is the sum of the training set losses.

3. Experiment and Analysis

3.1 Data set and Evaluation Indexes

The paper uses the first 400 Hokkaido F3 seismic data as the training set. The Gaussian noise with fixed level is added to it to generate noisy data; another 100 data as the test set. We use subjective

and objective ways to evaluate the results of noise suppression: the subjective evaluation method is to use the visual difference to the image to analyze the noise suppression effect; the objective evaluation method is to evaluate the image evaluation indexes, here we use two indexes to evaluate image quality, including peak signal-to-noise ratio (PSNR) and structural similarity (SSIM).

3.2 Suppression results of Random Noise of Synthetic Data

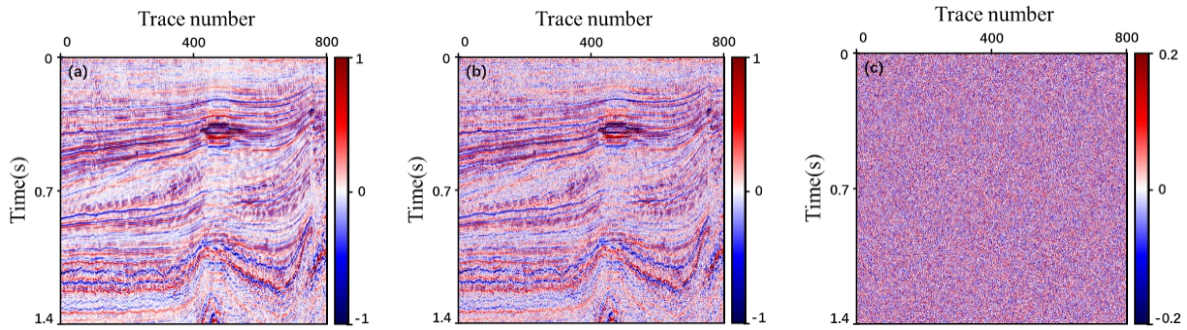


Fig. 3 (a) data without noise; (b) data with noise; (c) noise;

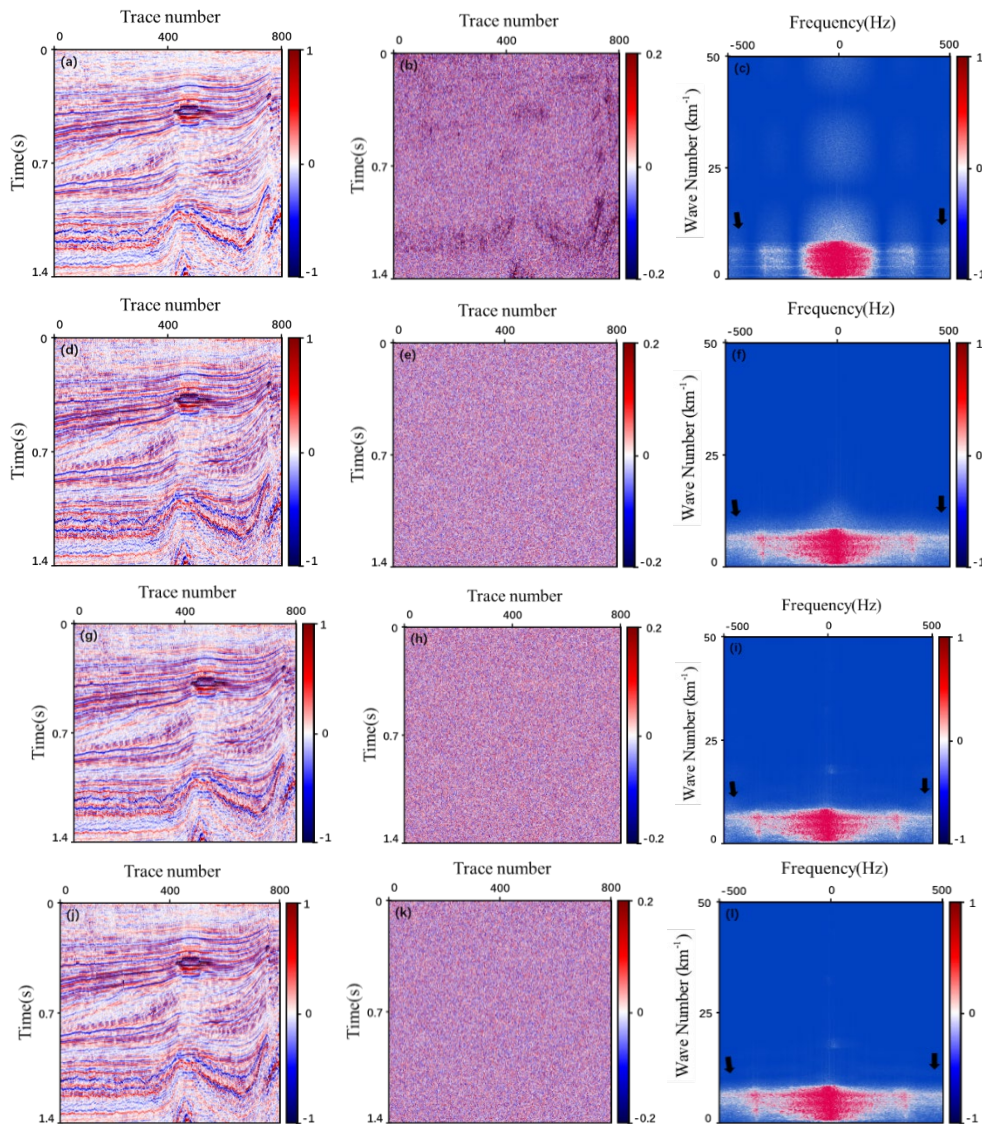


Fig. 4 method comparison of denoising results: (a) median filtering, (d) U-Net, (g) CNN, (j) MEU-Net; difference: (b) median filtering, (e) U-Net, (h) CNN, (k) MEU-Net; FK spectra: (c) median filtering, (f) U-Net, (i) CNN, (l) MEU-Net

In order to test the denoising effect of MEU-Net, we compare the denoising results of the model and the model used in this paper, as shown in Fig.3. Fig.3a is seismic data without adding random noise. Fig.3b is the result of adding random noise of Fig.3a, and Fig.3c is the added random noise.

Fig.4a, Fig.4d, Fig.4g, and Fig.4j are the denoising results of median filtering, CNN, U-Net, and MEU-Net, respectively; Fig.4b, Fig.4e, Fig.4h, and Fig.4k are the differences of median filtering, CNN-Net, U-Net, MEU-Net, respectively; Fig.4c, Fig.4f, Fig.4i, and Fig.4l are the FK spectra of the denoised data of median filter, CNN-Net, U-Net, and MEU-Net, respectively.

We can see that the median filter damages more effective signals by comparing the denoising results and removing noise. The other three methods achieved good results. But as can be seen from the FK spectra in Fig. 4f (CNN) and Fig. 4i (U-Net), the two methods still have residual noise (as shown by black arrows). Fig.4l (MEU) has the best denoising effect, there is almost no noise residue in the FK spectra.

We carry out denoising tests with different noise intensities on another 100 seismic data not participating in training, and calculate the average PSNR and SSIM of the data at the same time. Table.1 shows the denoising test results of different models under different levels of noise. The process is as follows:

The peak signal-to-noise ratio (PSNR) is:

$$PSNR = 20 \lg \frac{\max(x)}{\sqrt{MSE}} \quad (9)$$

And

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \|x(i, j) - \hat{x}(i, j)\|^2 \quad (10)$$

In the formula: n is the time sampling interval of the seismic data; m is the track number of the seismic data, x is the seismic data, $\hat{x}$ is the denoised data, $\max(x)$ is the maximum amplitude of the seismic data.

SSIM is:

$$SSIM(x, \hat{x}) = \frac{(2u_x u_{\hat{x}} + C_1)(2\sigma_{x\hat{x}} + C_2)}{(u_x^2 + u_{\hat{x}}^2 + C_1)(\sigma_x^2 + \sigma_{\hat{x}}^2 + C_2)}$$

In the formula, u_x and $u_{\hat{x}}$ are the mean value of x and $\hat{x}$, respectively; σ_x^2 and $\sigma_{\hat{x}}^2$ are the variance of x and $\hat{x}$, respectively; $\sigma_{x\hat{x}}$ is the covariance of x and $\hat{x}$; C_1 and C_2 are constants.

Table 1. Comparison of evaluation indexes of different denoising methods

noise intensity/dB	denoising algorithm	PSNR/dB	SSIM
5	Median filer	25.77	0.689
	CNN-net	33.19	0.889
	U-net	33.77	0.895
	MEU-Net	34.00	0.902
10	Median filer	24.84	0.598
	CNN-net	29.29	0.754
	U-net	29.84	0.774
	MEU-net	30.00	0.779
15	Median filer	23.62	0.501
	CNN-net	27.21	0.650
	U-net	27.75	0.674
	MEU-net	27.92	0.680

By adding noise with different intensities, the average peak signal-to-noise ratios of the data to be denoised are: 25.18dB (5%), 19.55dB (10%), 16.33dB (15%), average SSIM is: 0.669, 0.378, 0.228. The four algorithms all improve peak signal-to-noise ratio and SSMI on data to be denoised all improved, but the raising of MEU-Net is greater, so the MEU-net model has better denoising effect, it has certain advantages in improving the signal-to-noise ratio, and can be widely used in seismic data denoising.

4. Summary

This paper proposed the MEU-net network for the first time, this network can capture the seismic data features under different perception horizons by introducing the traditional backbone feature extraction and enhancement feature extraction module. Furthermore, we added the multi-scale enhancement module to further improve the denoising effect; in this module, we used dilated convolution to obtain different perceptual visual field, introduced the residual module to alleviate the gradient explosion and gradient disappearance, finally, made different weights are obtained among different features through the attention mechanism. The advantages of the above multi-scale enhancement module combined with the original network, made feature learning of random noise in seismic data of MEU-Net closer to the essential features of noise. By comparing median filtering, CNN and U-net, MEU-Net can better remove noise while protecting valid signals. The trained MEU does not require parameter adjustment and can be widely used in seismic data denoising.

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