DESERT LOW FREQUENCY NOISE SUPPRESSION BASED ON MULTI-LEVEL WAVELET CONVOLUTION NEURAL NETWORK

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ABSTRACT

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Due to the effect of various environment factors, the random noise in desert seismic exploration has complex characteristics, including low frequency, non-Gaussian and frequency band aliasing of signal and noise. Therefore, it is difficult for the denoising processing. Aiming at this problem, a Multi-level Wavelet Convolution Neural Network (MWCNN) is proposed to suppress the desert noise. MWCNN is a combination of two-dimensional discrete wavelet transformation and convolution neural network. Specifically, Discrete Wavelet Transformation (DWT) and inverse wavelet transformation (IWT) are used to replace the pooling layer and up-convolution of U-net respectively. So that the trade-off between receptive field and computational efficiency can be achieved. Consequently, the expansion of the receptive field can obtain more overall information of the events. In this paper, by adjusting the training set and structure of MWCNN, it is applied to suppress the random noise in desert seismic exploration. Furthermore, compared with other neural networks, MWCNN achieves better better denoising effect and better events' continuity by enlarging the receptive field in desert seismic records. And experiments on simulated synthetic records and actual seismic records respectively show our trained MWCNN model achieve a satisfactory denoising performance for the random noise in desert seismic exploration.

KEY WORDS: random noise, denoising, convolutional neural network.

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INTRODUCTION

The random noise of the seismic signal in desert area is complicated and unpredictable. It is always randomly distributed in both the time domain and the spatial domain, moreover, its frequency band are mixed with the frequency band of the signal. These characteristics impact the denoising processing seriously. Since the seismic data with a high signal-to-noise ratio (SNR) is the premise of the subsequent analyzing, such as studying the stratigraphic structure and attribute analysis, so improving SNR is an important link in seismic signal processing. However the characteristics of random noise are quite different from the Gaussian noise, so some methods suitable for removing the Gaussian noise can not completely suppress random noise. At present, some methods are widely used in seismic data processing such as f-x deconvolution (Harris et al., 1997), wavelet transform (Cao et al., 2005; Wang et al., 2016), direction control filter (Li et al., 2016), sparse dictionary learning (Zhang et al., 2017), etc.. Although the above traditional methods can improve the quality of seismic records to a certain extent, aiming at the complexity of desert seismic noise, the effect of these traditional methods is insignificant and the denoising parameters need to be adjusted manually. Meanwhile, these methods often have the deficiency in the amplitude preservation of effective signal and can't suppress the random noise thoroughly, so these methods are difficult to meet the need for modern high-precision detection and and it is urgent to find a more intelligent denoising method.

In recent years, Hinton put forward the concept of deep learning. The deeper layers and stronger learning ability of deep artificial neural network make the application of neural network widespread. So far, neural network has developed into a variety of models, such as deep belief network, convolution neural network (CNN) and generative adversarial network. Because of the local connection and weight sharing mechanism of CNN, it has been widely used in image classification (Krizhevsky et al., 2012), feature fusion (Tang et al., 2016), and image segmentation (Zhang et al., 2015). At the same time, it has been applied in some fields of seismic exploration. Zhao et al. (2019) applied CNN to classify and recognize the seismic waveform. Huang et al. (2017) applied CNN to seismic fault detection, and achieved good effect. In terms of denoising, Jain (2008) first proposed the natural image denoising with CNN in 2008, and achieved similar results with traditional methods. In 2017, Zhang et al. (2017) proposed a deeper CNN network called DNCNN. It has achieved excellent results at different noise levels, which shows that CNN has a good ability to learn noise characteristics.

In this paper, an improved convolution neural network is introduced to denoise the desert random noise (Liu et al., 2018). In our network, the pooling layer and the up-convolution of U-net (Ronneberger et al., 2015) is replaced by the DWT and IWT, so as to solve the drawbacks of sampling distortion in the pooling layer and the trade-off between the receptive field and the training difficulty. According to the simulation experiment and actual record processing, the good denoising effect manifests the that the introduced network is suitable for suppressing the random noise in the desert seismic signal.

MULTI-LEVEL WAVELET DENOISING CONVOLUTION NEURAL NETWORK

Network structure

As shown in Fig. 1, it is the network structure of MWCNN, which is proposed on the basis of U-net. Firstly, the four filters LL, LH, HL, HH are deployed to process signal by using the DWT. The four filters represent the high-frequency and low-frequency components in the vertical and horizontal directions respectively. This is a process of sampling and compression, which is equivalent to the role of the pooling layer in U-net. Then it is composed of four layers of full convolution network (FCN) without pooling layers. Each layer is composed of 3*3 convolution layer, batch normalization layer and correction linear unit connected in turn. The convolution layers of U-net will increase the number of feature channels. The difference is that MWCNN will increase the number of feature channels in the first layer of convolution layers. And other convolution layers will not increase the number of feature channels. It increase the number of feature channels in the DWT. Then the IWT replaces the up-convolution process of U-net, but it is different from the lossy process of the pooling layers and the up-convolution layers. Due to the biorthogonal nature of DWT, the original signal can be reconstructed accurately and error-free according to the four components of decomposition, so it is expected to achieve better denoising effect by MWCNN. In addition, similar to the pruning and merging of U-net network to achieve shallow feature fusion, MWCNN uses the element summation method to combine the feature graph of the contracting and expanding sub-networks.

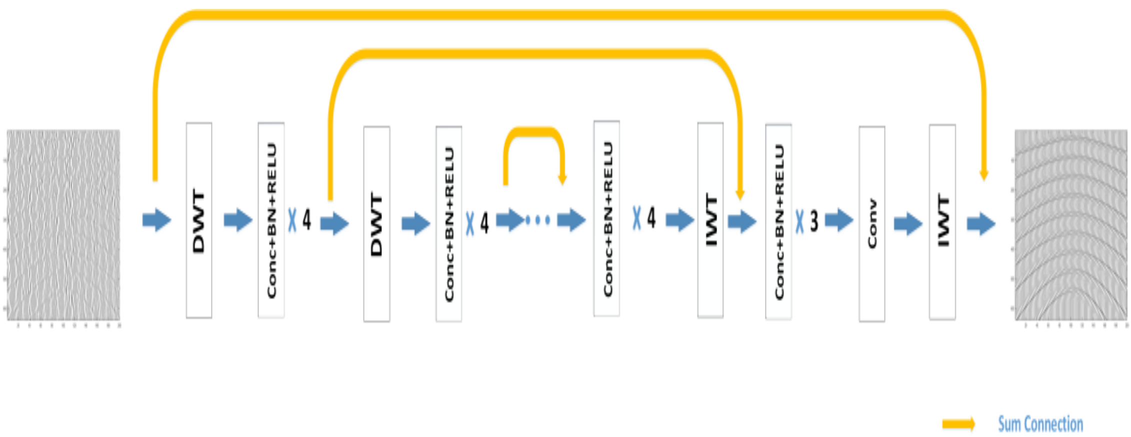


Fig. 1. MWCNN model.

Computational efficiency and performance are considered. The network structure of MWCNN is shown in Fig. 2. As shown in the figure, a three-level contracting and expanding sub-networks are adopted, and the CNN blocks at each level are composed of four layers of FCN without pooling layers. The first convolution layer of the first level contracting sub-network uses a filter size of 3*3*4*160 and the other three use 3*3*160*160. The last convolution layer of the first level expanding sub-network uses a filter size of 3*3*160*4. The first convolution layer of the second level contracting sub-network uses a filter size of 3*3*640*256 and the other three use 3*3*256*256. The last convolution layer of the second level expanding sub-network uses a filter size of 3*3*256*640. The first convolution layer of the third level contracting sub-network uses a filter size of 3*3*1024*256 and the other three use 3*3*256*256. Then the last convolution layer of the third level expanding sub-network uses a filter size of 3*3*256*1024. Finally, a 24-layer MWCNN network structure is formed.

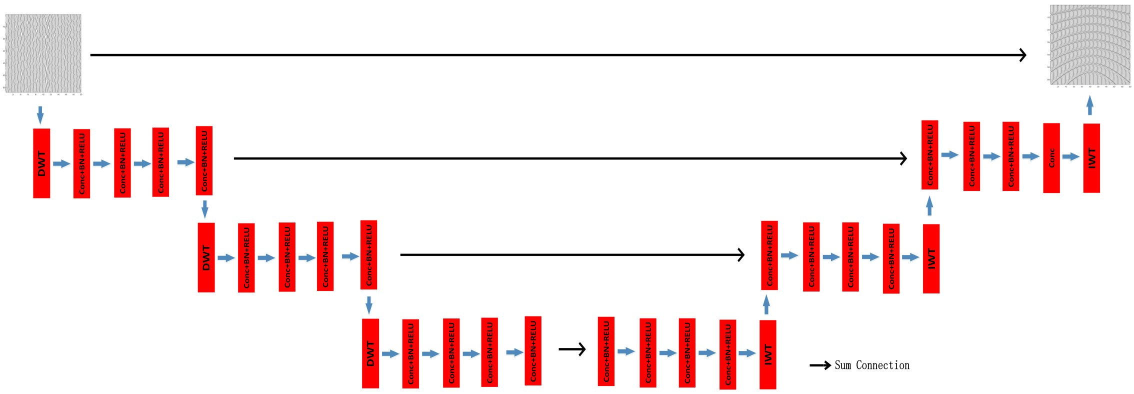


Fig. 2. 24-layer MWCNN structure.

Denoising Principle

At present, MWCNN mainly eliminates the Gaussian noise in the image, so the noisy signal is represented as:

$$y = x + n \quad , \tag{1}$$

among them, x represents a pure image, n represents the interference of Gaussian noise, and y represents the image of noise pollution. MWCNN does not adopt the method of residual learning. θ represents the parameters of MWCNN. $F(y,\theta)$ represents the output through the network, $\{y_i, x_i\}_1^N$ represents the training set, y_i represents the i-th noisy signal in the training set, and x_i represents the corresponding i-th pure signal. The following loss function is used in training:

$$L(\theta) = \frac{1}{2N}\sum_{i=1}^{N} \| F(y_i, \theta) - x_i \|_F^2 \quad . \tag{2}$$

ADAM (Kingma et al., 2014) algorithm is adopted to minimize $L(\theta)$. The parameters of ADAM are $\alpha = 0.01$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\varepsilon = 10^{-8}$, respectively. The other parameters of ADAM algorithm adopt the default values. It uses the initialization method proposed by Kaiming (2015) to initialize the parameters of the network, so as to solve the problem that the inappropriate selection of the initialization parameters leads to the increasing difficulty of training.

Production of training set

The random noise in desert seismic record is very different from the Gaussian noise, and the seismic events are also different from pictures. It is necessary to make pure signal set and corresponding noise set to suppress random noise from desert seismic data. For a pure set of signal, seismic events are usually short-term impulsive vibration generated by a source that propagates through the stratum. The most widely mathematical model of a seismic wavelet proposed by Ricker is called the Ricker wavelet. Its mathematical expression is as follows:

$$x = A(1 - 2\pi^2 f_m{}^2 \times t^2) \times e^{-\pi^2 f_m{}^2 t^2} \tag{3}$$

in the formula, A represents the maximum amplitude of the Ricker wavelet and f_m represents the main frequency of the Ricker wavelet. And using the frequency 15-30 Hz and propagation speed of 500-7000 m/s Ricker wavelets makes 3000 simulated data of size 640*200. In addition, due to the input of data blocks, patches with the size of 192*192 and the step size of 15 are used to sample the above data, so as to obtain 60000 pure signal training set of 192*192. Next comes the construction of the most important noise set. The quality of the noise set directly affects the effect of denoising. In order to make the noise set better and richer, we make 20000 simulated desert random noise of size 640*200. Patches with the size of 192*192 and the step size of 150 are used to sample the above data. There is not only random noise in the actual seismic record, but also a certain amount of surface wave which is intercepted from the actual record is added to the noise training set. The random noise patches with a size of 192*192 are obtained which are about 60000.

The following is the process of implementing denoising training:

1) Batch training is adopted, 15 pairs of data are input for each batch, and data is extracted from signal set and noise set successively.
2) The input noise is n, and the large difference in the input noise amplitude

is not conducive to training. The maximum value of noise is assumed to be A, and n/A is used to standardize the noise, so that the noise is within the range of (-1,1).

3) At the same time, in order to ensure that the pure signal does not show a negative value, it is assumed that the pure signal input is x. Since the maximum amplitude of the Ricker wavelet is 0.5, (x+0.3) is used as the input of the pure signal.

In summary, the input of the network is $y = (x + 0.3) + 5 \times (n \div A)$, and 5 times of the random noise is used as the noise input. The label of the network is $(x + 0.3)$, assuming the output of the signal is y, y and $(x + 0.3)$ are input into the network to optimize the parameters.

Meanwhile, the SNR and mean square error (MSE) are used to test the ability of noise suppression and signal amplitude preservation.

$$SNR = 10\lg\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(X(i,j)-\overline{X})^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(Y(i,j)-X(i,j))^2}\right), \tag{4}$$

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(Y(i,j)-X(i,j))^2 , \tag{5}$$

among them, X represents the pure signal, M and N represents the number of sampling points and traces of the signal, $\overline{X}$ represents the average value of X , and Y represents the signal after processing.

SYNTHETIC EXPERIMENT

First, design a synthetic seismic record containing 400 traces with 640 sampling points per trace. As shown in Fig. 3(a), it is a simulated seismic record with the main frequencies of 20, 22, 23 and 25 Hz of ricker wavelets including linearity, curve, crossover and discontinuity. b is the added random noise of desert seismic record. In order to make the denoising effect extensive, the added random noise is not the noise in the training set. c is a noisy record with noise added, and the SNR is -9.8437 dB.

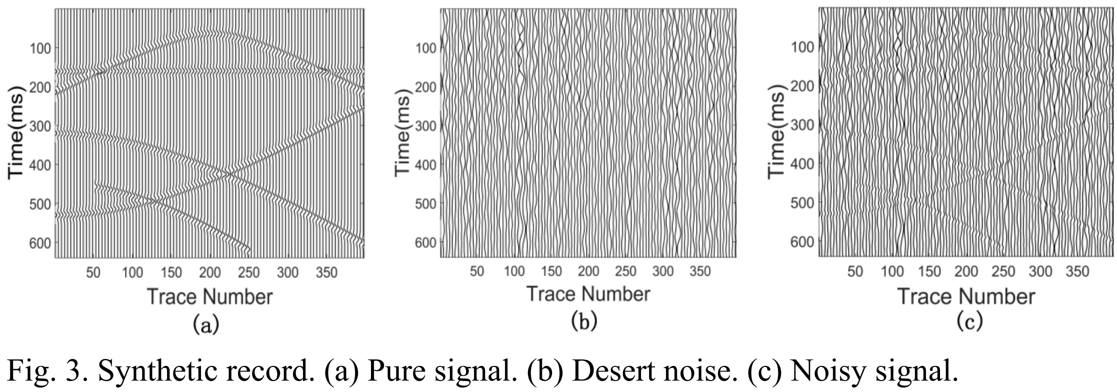


Fig. 3. Synthetic record. (a) Pure signal. (b) Desert noise. (c) Noisy signal.

Figs. 4 a, b, c are the corresponding F-K spectrum. As shown in Fig. 4, the signal and noise frequency have a certain overlap;

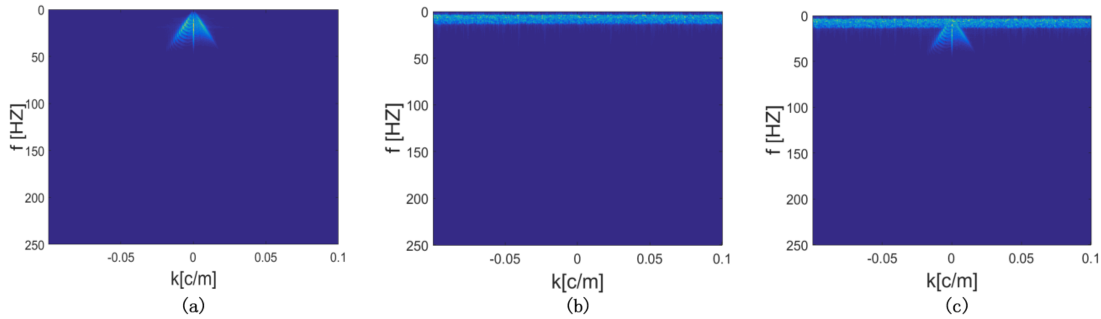


Fig. 4. F-K spectrum. (a) Pure signal. (b) Desert noise. (c) Noisy signal.

The trained model is validated with the simulated seismic record designed above. As shown in Fig. 5(a), the trained MWCNN model can effectively learn the characteristics of the events including the more complex crossover events. After denoising, the SNR is 16.5585 dB, which is about 25 dB higher than that of noisy record. Fig. 5(b) is the difference between noisy signal and predicted signal, and it can be seen that there is no residual signal in the difference.

We take the 30th trace and 150th trace for single-trace comparison in Fig. 6. From the result of single trace, it can be seen that the pure signal and denoised signal basically coincide, which shows that the trained MWCNN has good performance in denoising and amplitude preservation.

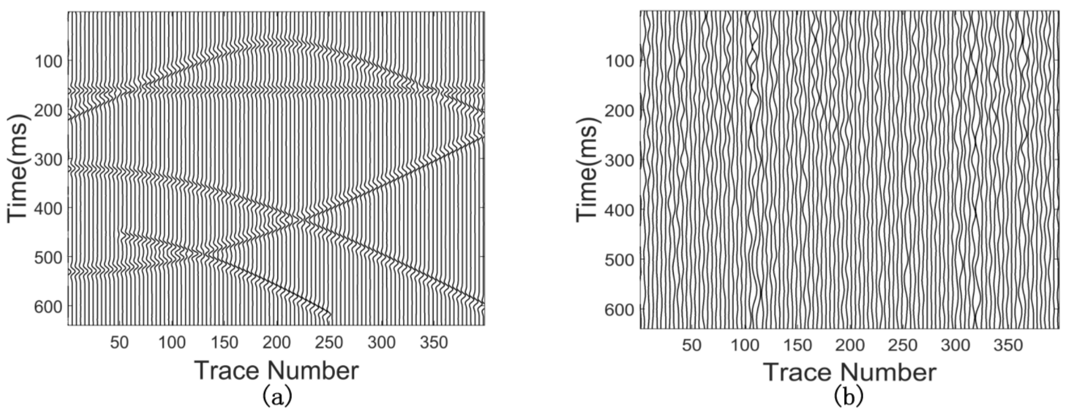
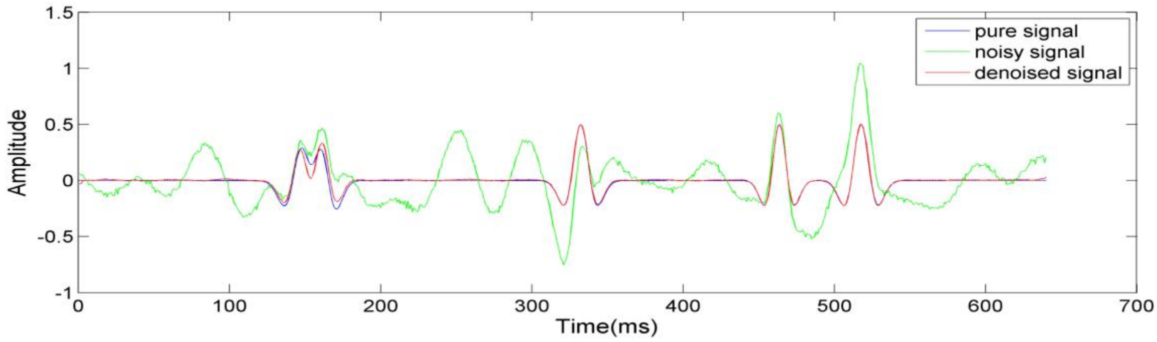
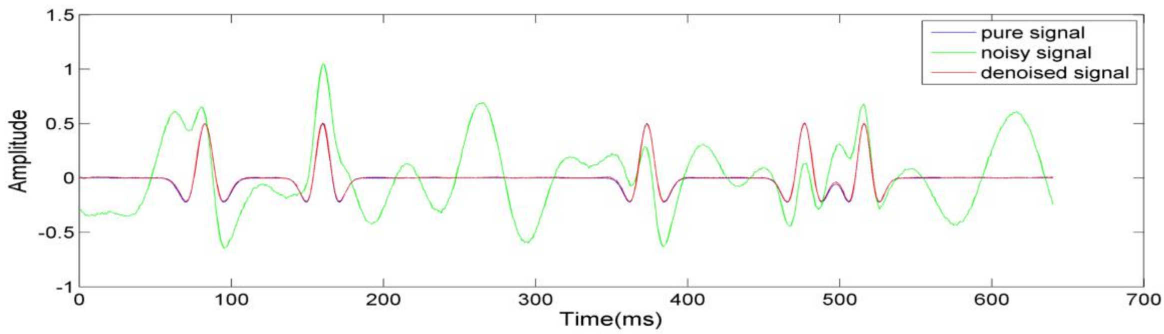


Fig. 5. MWCNN denoising results. (a) The denoising result. (b) Difference value.



（a）



（b）

Fig. 6. Single-trace comparison. (a) The 30th trace. (b) The 150th trace.

In order to further illustrate the advantages of MWCNN, we compared with some traditional methods. The a, b, c, d and e in the Fig. 7 are the pure signal, wavelet transform, f-x deconvolution, band-pass filter and the results of trained MWCNN processing. Fig. 8 is corresponding F-K spectrum after denoising by various methods. It can be seen that compared with the three methods, the frequency distribution of the signal after the denoising of the trained MWCNN is closer to that of the pure signal, which indicates that the trained MWCNN can more accurately predict the effective signal.

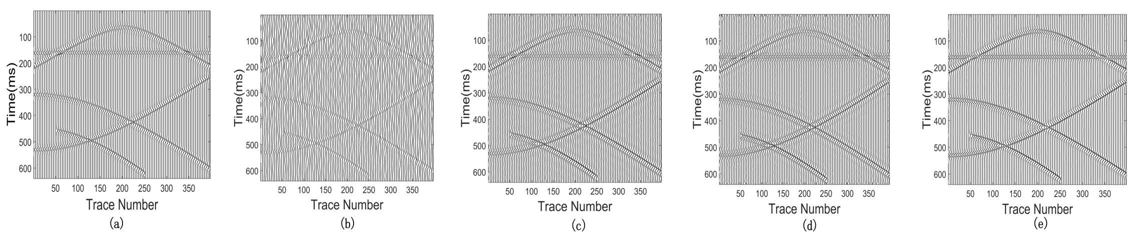


Fig. 7. Denoising result. (a) Pure signal. (b) Wavelet transform. (c) F-X deconvolution. (d) Band-pass filter. (e) Trained MWCNN.

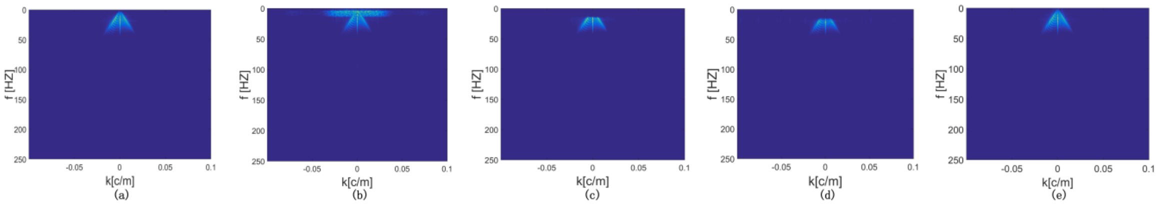


Fig. 8. F-K spectrum. (a) Pure signal. (b) Wavelet transform. (c) F-X deconvolution. (d) Band-pass filter. (e) Trained MWCNN.

In addition, in order to test the ability of the trained MWCNN to suppress random noise blindly, the trained MWCNN model and three other methods are used to process 10 data with different intensity of desert noise. SNR and MSE are used to measure the ability of noise suppression and signal amplitude retention. As shown in Table 1, we can see that the trained MWCNN is better than the previous three methods. The SNR is obviously improved and the MSE is very small, which indicates that there is basically no energy loss in the signal.

Table 1. Noise reduction results of several methods with different noise levels.

Original data		Wavelet transform		F-X deconvolution		Band-pass filter		Trained MWCNN	
SNR (dB)	MSE	SNR (dB)	MSE	SNR (dB)	MSE	SNR (dB)	MSE	SNR (dB)	MSE
0.7859	**0.0127**	**6.7007**	**0.0033**	**5.6496**	**0.0042**	**4.2808**	**0.0057**	**17.0617**	**0.000299**
-5.2347	**0.0509**	**0.7202**	**0.0129**	**5.5687**	**0.0042**	**4.2308**	**0.0058**	**16.9517**	**0.000307**
-9.6717	**0.1413**	**-3.7082**	**0.0358**	**5.4504**	**0.0043**	**4.1144**	**0.0059**	**16.5877**	**0.000344**
-11.2553	**0.2035**	**-5.2909**	**0.0515**	**5.3856**	**0.0044**	**4.0363**	**0.006**	**16.235**	**0.000362**
-12.5942	**0.277**	**-6.6326**	**0.0702**	**5.3158**	**0.0045**	**3.9457**	**0.0061**	**15.9811**	**0.000384**
-13.754	**0.3618**	**-7.8022**	**0.0919**	**5.2408**	**0.0046**	**3.8435**	**0.0063**	**15.8232**	**0.000398**
-14.7771	**0.4579**	**-8.8457**	**0.1168**	**5.1606**	**0.0046**	**3.7305**	**0.0065**	**14.2075**	**0.000578**
-15.6933	**0.5653**	**-9.7934**	**0.1453**	**5.0756**	**0.0047**	**3.6076**	**0.0066**	**14.1997**	**0.000579**
-16.5201	**0.684**	**-10.6666**	**0.1777**	**4.9862**	**0.0048**	**3.4757**	**0.0068**	**12.2981**	**0.000897**
-17.2759	**0.814**	**-11.4803**	**0.2143**	**4.893**	**0.0049**	**3.3357**	**0.0071**	**11.2946**	**0.00011**

ACTUAL DATA PROCESSING

In order to verify the effect of suppressing random noise in actual records, we select a field desert seismic record for processing. As shown in Fig. 9(a), it is a common shot point seismic record containing 183 traces and each track contains 1300 sample points. The sampling frequency is 500 Hz. Fig. 9(e) is the result of using MWCNN processing. At the same time, we compare it with the traditional methods. Fig. 9(b) is the result of wavelet transform, 9(c) is the result of f-x deconvolution and 9(d) is the result of band-pass filtering.

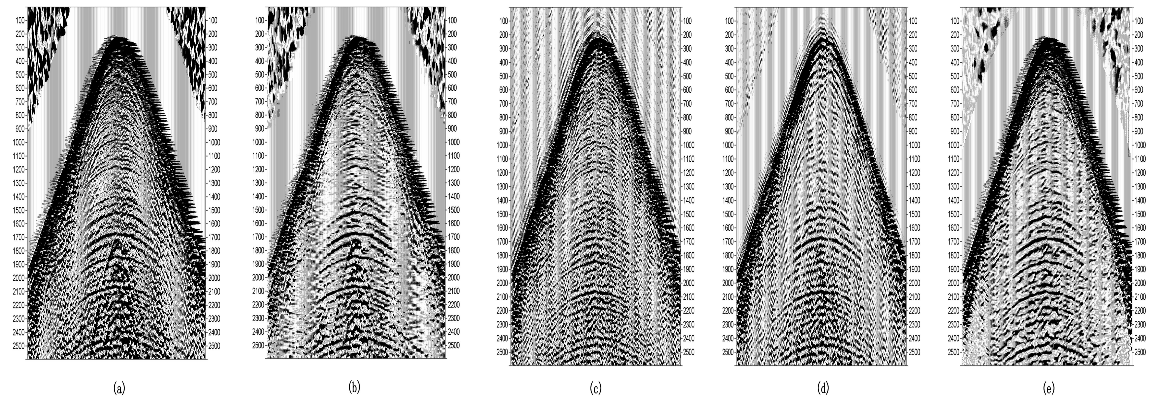
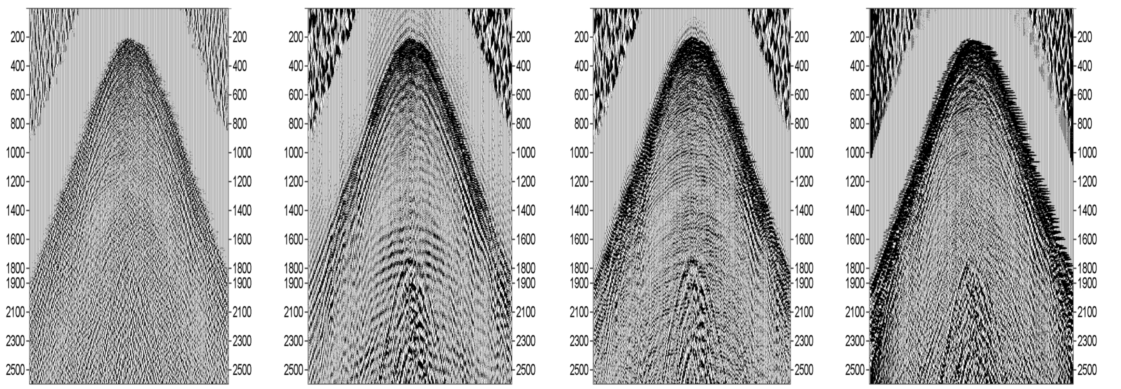


Fig. 9. Processing results. (a) Original record. (b) Wavelet transform. (c) f-x deconvolution. (d) Band-pass filter. (e) Trained MWCNN.

After observing the original record and the results after several times of processing, the f-x deconvolution has a good effect of suppressing surface wave, but the ability of suppressing random noise is poor, leading to events still submerged in noise. The wavelet transform and band-pass filter can suppress certain random noise and the events also has good continuity, but there is a lack in the suppression of surface wave. The band-pass filter suppresses a certain amount of surface wave, but the suppression is not very thorough. The wavelet transform has no effect in the suppression of surface wave. By observing the result of the trained MWCNN processing, it has a good effect in suppressing the surface wave and random noise, and does not lose the continuity of the events.

In order to better reflect the superiority of the trained MWCNN in suppressing random noise, we deal with the difference of various methods. As shown in Figs. 10, a, b, c, d are the difference images between the denoising results of the above methods and the original record.

It can be seen from the difference of various processing methods that there are some signal residues in the difference between f-x deconvolution and band-pass filter processing, which indicates that there are some deficiencies in the amplitude preservation of the two methods. Then it can be seen from the result of wavelet transform difference. Although there is no noise residue, the color of the difference image looks lighter and the noise amplitude is small. It shows that the ability of suppressing random noise is poor. Looking at the difference after MWCNN processing, there is basically no residual signal and the complete surface wave in the difference figure shows that the surface wave suppression effect is also good.



(a) (b) (c) (d)

Fig. 10. Difference results. (a) Wavelet transform. (b) F-X deconvolution. (c) Band-pass filter. (d) Trained MWCNN.

In summary, through the simulation and actual data testing, our trained MWCNN model has better effect in suppressing random noise and surface wave than other traditional methods, and basically there is no loss of amplitude in the signal.

CONCLUSION

In this paper, MWCNN is improved to suppress the random noise in the desert seismic exploration. To sum up, compared with some traditional methods, it has the following advantages:

1) The introduction of discrete wavelet transformation by MWCNN enables it to have a larger feeling field when the training difficulty is the same as that of other networks, so that more comprehensive information of the effective signal can be obtained, that is, our method can improve the continuity and integrity of the retained signal;
2) MWCNN has the universal applicability. In the process of suppressing the noise with different intensity, the trained MWCNN model with single intensity of the desert noise obtained better denoising effect and amplitude preservation than the traditional methods.

3) The trained MWCNN not only suppresses the random noise effectively, but also suppresses the surface wave in the actual record, which is more advantageous than the traditional methods for the actual records in which the events are submerged in the surface wave.

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