Introduction

Seismic exploration is a significant way for probing subsurface structures to explore oil and gas resource. However, complicated geological condition in desert area causes the raw seismic data having low signal-to-noise ratio (SNR). In addition, the desert seismic random noise has similar waveform with seismic signals and the frequency band of both also is overlapping, making identification of seismic signals extremely difficult. Therefore, noise reduction is one of the important topics in seismic data processing. To improve the quality of seismic data, various denoising methods have been developed (Anvari et al., 2017; Liu et al., 2018). But, although those denoising methods highly enhance the quality of seismic data, denoising performance is still needed to be improved in the case of low SNR. Recently, as computer hardware improves, some novel neural network architectures have been explored, while convolutional neural network (CNN) is one of the most important types. The larger CNNs can be trained and resulting wide applications in various fields have achieved outstanding performances (Zhang et al., 2017; Zhang et al., 2018). In seismic data processing, researchers have applied the CNNs to signal restoration (Zhao et al., 2019; Zhu et al., 2019; Zhao et al., 2020). But, there still are few existing problems looking specifically at CNNs used in field seismic noise attenuation. The denoising performance of learned model is largely dependent on the training data. However, due to the lack of ideal field seismic data for training, most of the training data sets are constructed by synthetic seismic data or the preprocessed field seismic data provided by traditional seismic denoising methods. There resulting models will have some adaptability limits in denoising field desert seismic data and the denoising performance is needed to be improved. Zhang (2017) utilized a set of effective CNN models as the denoiser prior and integrated them into model-based optimization method to solve different inverse problems which not only reserves the flexibility for handling different inverse problems belonging to model-based optimization method but also utilizes the CNN model to deliver good performance.

Inspired by this integration, we consider to combine the CNN model with the complex shock diffusion (CSD) (Gilboa et al., 2004) for improving the performance of field seismic data processing. The CSD based on the partial differential equation is a nonlinear complex diffusion process and also has the flexibility for different data processing problems by incorporating a reaction term. Therefore, we integrate the CNN model with CSD by means of plugging the CNN model into the additive reaction term of CSD and propose the complex diffusion coupled CNN (CD_CNN) method. For denoising processing, through the iterated diffusion of the proposed CD_CNN, the desert seismic random noise is gradually removed. Meanwhile, the additive reaction term adds the desired residual signal components learned by the CNN model. The CD_CNN implements the complementary advantages of the CNN model based on learning and non-learning based diffusion method, for achieving better denoising results. Through testing on the synthetic and field desert seismic data, it is demonstrated that the CD_CNN shows superior performance in noise attenuation and signal protection.

Theory

The goal of denoising is to recover the underlying signal \( X \in \mathbb{R}^{m \times c} \) from a noisy observation \( Y \) which follows a degradation model, and \( V \) is the additive random noise. The model based denoising is a conventional neural network trained by a residual learning framework. The input of the denoising conventional neural network (DnCNN) is the noisy data \( Y \) and the aim of DnCNN is to learn the residual mapping \( F(Y) \approx V \). In this way, the denoised data can be obtained as \( X = Y - F(Y) \). The architecture of the DnCNN with deep \( L \) used in our work contains three types of layers (Zhang, 2017). (i) Conv+ReLU: as the first layer of the network, the convolution having 64 feature maps with size \( 3 \times 3 \) is utilized and the following rectified linear units (ReLUs) are then employed for nonlinearity. (ii) \( s \)-Conv+BN+ReLU: for layers 2-(\( L-1 \)), 64 dilated filters with size \( (2s + 1) \times (2s + 1) \times 64 \) are used in the convolution (\( s \geq 2 \)). Batch normalization (BN) is added between convolution and ReLU during training, in order to accelerate the speed of convergence and improve the denoising performance by cooperating with residual learning. (iii) Conv: a separate convolution as the last layer with size \( 3 \times 3 \times 64 \) is set to reconstruct the output of the network. The DnCNN adopts residual learning framework to learn parameters in each layer by minimizing the loss function which is the averaged
mean squared error between the residual noise data and estimated ones from noisy data for $N$ training samples. The formula of loss function is written as
\[
\ell(\Theta) = \frac{1}{2N} \sum_{p=1}^{N} \| O(Y_p, \Theta) - (Y_p - X_p) \|^2
\]
where $(Y_p, X_p)_{p=1}^{N}$ represents $N$ noisy-clean training pairs. $O$ is the output of the network, and $\Theta$ is all trainable parameters in the network. The DnCNN predicts residual noise rather than the latent signals based on the residual learning. However, the CNN model trained by the synthetic seismic data has some adaptability limits in denoising field desert seismic data which is caused by the lack of ideal field seismic data for training. In this work, based on the CNN model trained by the synthetic seismic data available, we propose to fuse non-learning based diffusion term of CSD with learning-based reaction term provided by CNN model to construct a reaction diffusion model. In case of denoising, the formula of the proposed method in the stage $n+1$ is given as follows:
\[
X^{n+1} = X^n + \Delta t \left[ \frac{2}{\pi} \arctan(a \ln|X^n/\theta|) \nabla X^n + \lambda X_{n+1}^{||} + \lambda X_n^{\perp} + \mu (X^{n} - X_C^{n}) \right] \quad (n = 0, 1, 2, \ldots)
\]
where $X^{n+1} = Y$, $X_{n+1}^{||} = X_n^{n} - F(X^n)$. The result $X^{n+1}$ is generated by the iterative denoising process in the stage $n+1$. The parameter $\mu$ can be adjusted to control the weight of reaction term. The flowchart of the proposed method also is shown in Fig. 1. The diffusion term includes denoising part for removing random noise along with the iterative process and enhancement part provided by the shock filter. Meanwhile, the reaction term is constructed by the difference between the result predicted by the CNN model and the diffusion result for providing the information which is estimated by the CNN model and lost in the diffusion process. Through the fusion of each stage, the proposed method effectively combines the actual features of the seismic data delivered by the diffusion term and the predicted features of the seismic data introduced by the reaction term based on learning. By the coordination of the two terms, the CD_CNN improves the performances of removing seismic random noise in desert area and preserving signal textures.

**Figure 1.** The flowchart of the proposed method.

**Figure 2.** The filtered results of four methods after denoising synthetic noisy seismic data, and the difference data between the denoised ones with pure data. (a) Pure seismic data. (b) Noisy seismic data (SNR=-4.10 dB). (c) Result of the band-pass filter. (d) The difference of the band-pass filter. (e) Result after applying CSD. (f) The difference of CSD. (g) Result after using the DnCNN-B. (h) The difference of DnCNN-B. (i) Result of the proposed CD_CNN. (j) The difference of CD_CNN.
Consider the difficulty of the acquiring clean field seismic samples for training, we use the synthetic seismic signals as the pure training samples which are generated by the Ricker wavelet, zero-phase wavelet, and mixed-phase wavelet. The real desert noise with a wide range of noise levels covering our experiments is used to generate the noisy training samples, and a blind DnCNN model (DnCNN-B) whose depth is 9 and receptive field size is 51×51 is obtained and used in our experiments.

To investigate the validity of seismic random noise attenuation of the CD_CNN, we employ it and the other three methods (bandpass filter, CSD, and DnCNN-B) to denoise the synthetic and field desert seismic data. The synthetic seismic data consist of six seismic events whose dominant frequencies include 20Hz, 15Hz, 12Hz, 10Hz, and 8Hz shown in Fig. 2(a). The real desert noise is added to the pure seismic data, making the noisy seismic data have the SNR of -4.13dB [Fig. 2(b)]. The filtered result [Fig. 2(c)] applied by the bandpass filter still remains plenty of desert seismic noise due to the fact that desert random noise and seismic signals are blending on the frequency band. In Fig. 2(e), although many random noise has been removed by the CSD, some seismic signals are not able to be recovered which is caused by the waveform similarity of desert random noise and seismic signals, disturbing the diffusion process. For the DnCNN-B, the filtered result is better than the bandpass filter and CSD method. The desert random noise is almost reduced and the effective signals have been well preserved, which also can be validated in Fig. 2(h). The result indicates that the learned DnCNN-B has a denoising capacity for synthetic seismic data corrupted by real desert noise. In contrast with the other three methods, the CD_CNN [Fig. 2(i)] achieves the best denoising performance with minimal residual noise and signal attenuation, and the difference data also clearly verifies its effectiveness [Fig. 2(j)]. Moreover, we give quantitative comparisons of four denoising methods for different SNR experiments in terms of the signal noise ratio (SNR) and mean squared error (MSE) listed in the Table I. Comparing with the other three methods, the CD_CNN always achieves the highest SNR and lowest MSE.

We further verify the effectiveness of the CD_CNN for denoising field seismic record. We select a 218-trace common-shot-point seismic record from the desert area which contains 1620 samples in each trace, shown in Fig. 3(a). The sampling frequency is 2kHz. The banpass filter, CSD, and DnCNN-B also are applied to this noisy record. Fig. 3(b)-(e) represent the denoised results of the bandpass filter, CSD, DnCNN-B, and CD_CNN, respectively. The four filtered results show that plenty of desert random noise has been reduced by the CSD and CD_CNN while the bandpass filter and DnCNN-B have more random noise residual. In Fig. 3(d), although the DnCNN-B can not attenuate some field seismic noise, seismic events are preserved well, especially the steeply dipping seismic events. Fig. 3(e) indicates that the CD_CNN does better in removing desert random noise and protecting signals than the DnCNN-B and CSD. For a better visualization and comparison, we zoom in one typical area [1240-2800 ms, 50-190 traces] from the noisy seismic data and denoised results, shown in Fig. 4. As can be seen in Fig. 4, the bandpass filter has the worst denoising performance among the four approaches. The DnCNN-B removes some desert random noise from the field seismic data, but is inferior to the CSD. Comparing to the other three methods, the proposed CD_CNN not only removes more random noise and makes the background cleaner, but also recovers the seismic events more effectively.

<table>
<thead>
<tr>
<th>Noisy SNR(dB)</th>
<th>SNR MSE</th>
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<th>SNR MSE</th>
<th>SNR MSE</th>
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<tbody>
<tr>
<td>-0.15</td>
<td>3.27 0.0490</td>
<td>9.63 0.0113</td>
<td>13.08 0.0051</td>
<td>14.14 0.0040</td>
<td></td>
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<tr>
<td>-4.13</td>
<td>0.70 0.0885</td>
<td>6.22 0.0248</td>
<td>9.11 0.0128</td>
<td>10.46 0.0094</td>
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</tr>
<tr>
<td>-7.51</td>
<td>-1.20 0.1372</td>
<td>4.21 0.0394</td>
<td>7.53 0.0184</td>
<td>8.82 0.0136</td>
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**Conclusions**

The CD_CNN is proposed to combine the leaning-based denoising convolutional neural network and the nonlinear complex diffusion method which is as a non-leaning method. The denoising convolutional neural network provides the learned information and feedbacks the effective signals lost in the diffusion process. We show the denoising feasibility that the CD_CNN reuses the learned DnCNN for synthetic and field seismic denoising applications and couples it with the CSD whose flexibility in denoising is reserved. From the experiments of synthetic and field seismic data, it is
demonstrated that the proposed CD_CNN produces favorable performance in removing seismic random noise in desert area as well as protects plentiful seismic signal textures.

Fig. 3. Denoised results of a field seismic record in desert area. (a) Noisy record. (b) Result of the band-pass filter. (c) Result of the CSD. (d) Result of the DnCNN-B. (e) Result after using the CD_CNN.

Fig. 4. Filtered result comparison of the selected region. (a) Noisy record. (b) Denoised by the band-pass filter. (c) Denoised by the CSD. (d) Denoised by the DnCNN-B. (e) Denoised by the CD_CNN.

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References