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Seismic Denoising by Supervised Deep Learning without Seismic Data

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Summary

Noise suppression is very important for the accuracy and reliability of processing results and their subsequent interpretation. We propose an effective denoising method for seismic data using a supervised deep learning strategy. The novel idea of the proposed framework is to learn to map noisy seismic data to clean signals by training noisy natural images without explicit signal or noise priors, avoiding constructing a complete and representative synthetic seismic dataset and collecting a large number of high quality noiseless field seismic data. This proposed strategy is very useful in real data processing. Tests on synthetic and real datasets demonstrate this proposed strategy achieves superior performance in terms of signal-to-noise ratio (SNR) enhancement.

Introduction

Attenuating random noise is of great significance in the processing of reflection seismic data (Zhang and Van der Baan, 2018). Deep learning based methods have been successfully applied in noise removal (Zhang et al., 2017; Saad, et al., 2018; Zhang and Van der Baan, 2019; Zhu et al., 2019). Unlike traditional methods, deep learning based denoising methods do not need to exploit signal or noise prior information and avoid tuning parameters of filters for the best possible results. Several factors play a key role in deep learning. One requirement is that training data must be both complete and representative. Clean targets are also crucial for high performance deep learning denoisers. However, acquiring clean training targets from a real dataset is often difficult or sometimes even infeasible. So synthetic noise-free data are commonly adopted in the training process. But it is difficult to generate a synthetic training set that includes all features of seismic events. In this paper, we demonstrate that training on noisy natural images can lead to highly successful seismic data denoising.The natural images contain numerous complex features, which likely surpass the complexity of seismic images. Yet, both natural images and seismic events are spatially correlated. So if we teach a neural network to map noisy natural images to clean ones, it will also be able to reconstruct seismic images by removing superposed noise. These images are noise free, allowing us to illustrate a technique known as noise injection as implemented by Lehtinen et al. (2018). We will only use noisy images both as input and output. Any network can be applied for training, for our tests, we use a shallower U-network (U-Net, Ronneberger et al., 2015) which is faster to train and gives similar results.

Method

For denoising, the form of the typical training task for a set of input-target pairs are the noisy-clean ones. But we replace them as noisy-noisy pairs in this paper. The empirical risk minimization task is written as (Lehtinen et al., 2018):

$$\arg\min_{\Theta}\sum_{i} L(F_{\Theta}(x_i), y_i), \tag{1}$$

where $F_{\Theta}(\cdot)$ represents the network function parameterized by Θ; L represents the loss function. Both input x_i and target y_i are contaminated with noise, conditioned on the underlying clean target $\hat{y}_i$ which are the same image but perturbed differently by added noise. Because numerous images are used repeatedly, on average the training error approaches zero, and the reconstruction becomes of a very high quality. For details, see Lehtinen et al. (2018).
A noisy seismic image $\mathbf{sn}$ is modeled by:

$$\mathbf{sn} = \mathbf{s} + \mathbf{n}, \tag{2}$$

where $\mathbf{s}$ is the clean image, and $\mathbf{n}$ is the additive noise. The implemented network learns the desired underlying mapping function from equation (1) using noisy natural images to predict the latent clean seismic image. Finally, the estimated clean seismic image $\hat{\mathbf{s}}$ is obtained from:

$$\hat{\mathbf{s}}=F_{\Theta}(\mathbf{sn}). \tag{3}$$

We use the adaptive moment estimation (Adam) solver (Kingma and Ba, 2015) to optimize the network parameters Θ. The mean square error (MSE) is adopted as a loss function.
The mapping function $F_{\Theta}(\cdot)$ in this framwork can be learned by any network. In this paper, $F_{\Theta}(\cdot)$ is learned by the U-Net (Ronneberger et al., 2015). The network architecture can be seen in Ronneberger et al. (2015).

Results

We first test the trained network on a 2-D synthetic data as shown in Figure 1a. The sample interval of this dataset is 1ms. We add strong white Gaussian noise to the synthetic model. The signal-to-noise ratio (SNR) of noisy record is -9.28 dB as shown in Figure 1b. We compare the proposed method with f-x deconvolution and the K-Singular Value Decomposition (KSVD) method.

The processing results of the three methods are shown in Figure 2. Some noise has been eliminated and the events are generally recovered by f-x deconvolution, but the residual low-frequency noise still destroys continuities of the events.The KSVD method suppress more noise than f-x deconvolution, but the energy of correlated signals are lost. The events are more clearly and continuously recovered by the proposed method, and there is less residual noise compared with the other two methods.

The performance of the proposed method is also verified on a common-shot-point record. This record contains strong random noise and it is shown in Figure 3a.The presence of incoherent noise obscures the continuity of reflections. Again, f-x deconvolution and the KSVD method are applied for comparison. Most noise can be attenuated by these three methods. Some events recovered by f-x deconvolution are less continuous and the energy of effective signals is attenuated. The energy of most events are better preserved by the KSVD method compared with f-x deconvolution, but some events are still disrupted by the residual noise. The proposed method achieves the cleanest background and all events are clearly recovered.

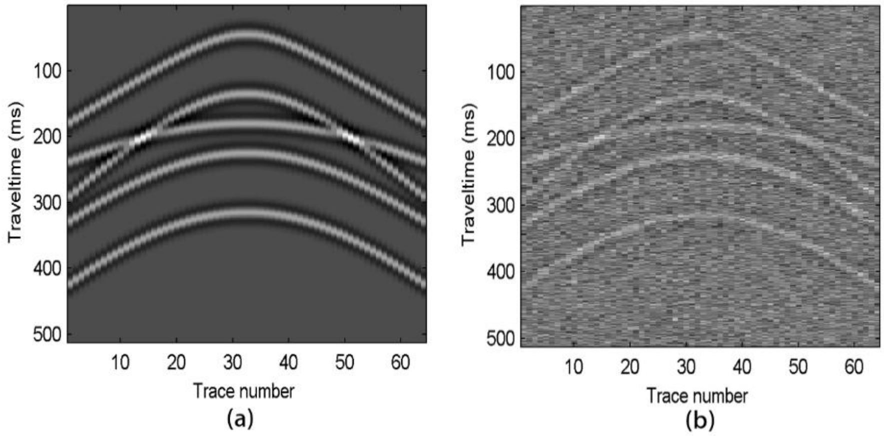

Figure 1: Synthetic records. (a) Noise-free data. (b) Data contaminated with random noise.

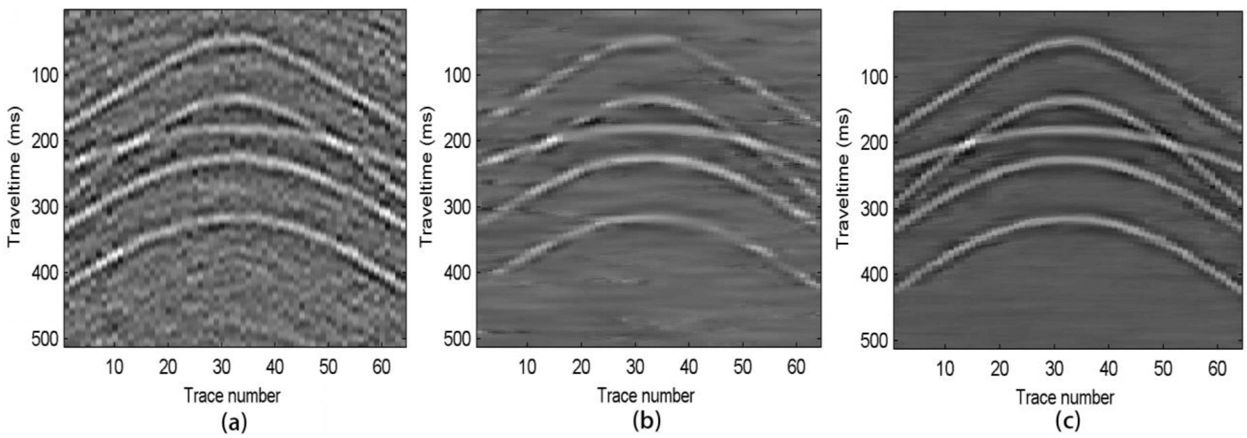

Figure 2: The noise-reduction results. Results after (a) f-x deconvolution, (b) the KSVD method, (c) the proposed method.

Conclusions

We exploit the inherent complexity that exists in natural images to create an effective denoising neural network for seismic data. Double noise injection overcomes the need for clean training images. Noise injection also helps in ensuring we have more training examples than free parameters in the neural network. We anticipate that adding seismic data to the training process may further enhance the reconstruction quality.

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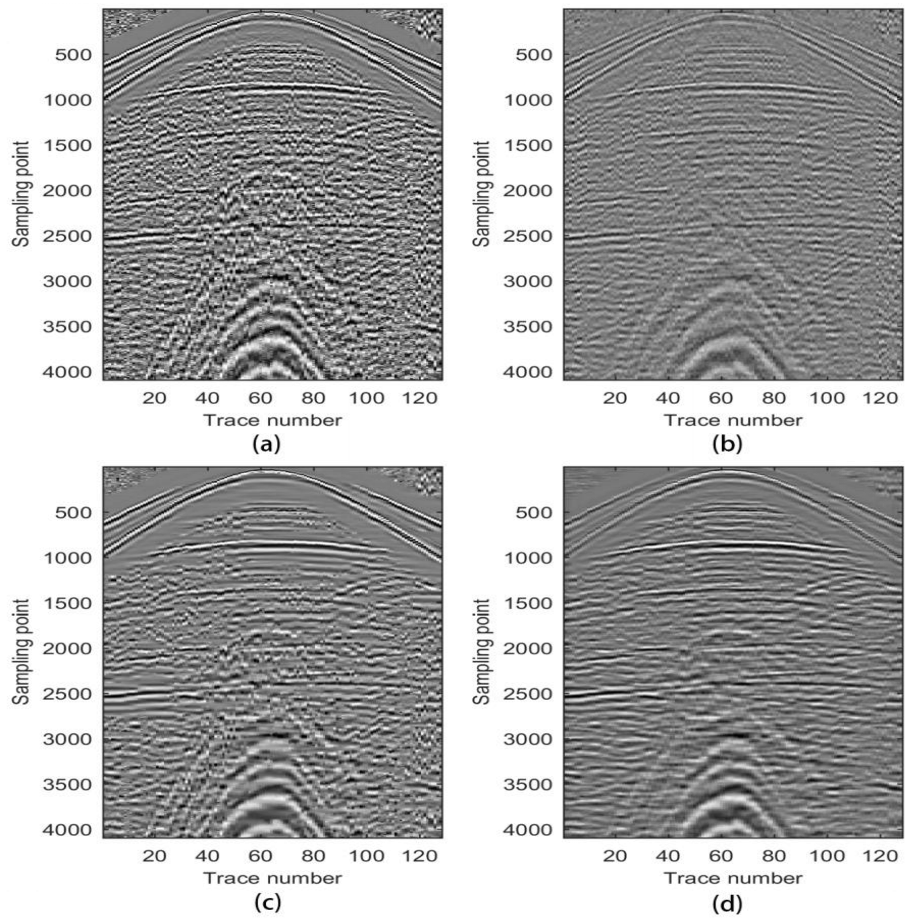

Figure 3: (a) A common shot gather.The noise-reduction results after (b) f-x deconvolution, (c) the KSVD method, (d) the proposed method.

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