From learning noise to denoise using deep convolutional neural network: an application of seismic noise attenuation

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Summary

Seismic noise attenuation is one of the important steps in seismic data processing. Most of the noise attenuation algorithms are based on the analysis of time-frequency features of the seismic data and noise. We propose to attenuate the noise of seismic data by learning the noise through convolutional neural network (CNN). Traditionally CNN based noise attenuation algorithms need "clean" data and the corresponding noisy data in the training process. However, it is very difficult to obtain the purely clean seismic data in practice. The proposed workflow assumes that the white noise contained in the seismic data can be simulated by a set of user-generated white noise. Thus, the proposed workflow does not require the "clean" seismic data and the corresponding noisy seismic data for training. We use both synthetic example and two field data examples to illustrate the robustness and superiority of the proposed method over two commonly used seismic denoising methods.

Theory

Objective function

The fundament of image denoising process is defined as $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{n}$, where $\boldsymbol{x}$ is the clean images, $\boldsymbol{y}$ is the corresponding noisy images and $\boldsymbol{n}$ is the additive white noise. The goal of image denoising is building a model to recover the clean images $\boldsymbol{x}$ from the corresponding noisy images $\boldsymbol{y}$. According to the type of objective function, the image denoising methods can be classified into two categories.

The first category is modeling the noise attenuation process by minimize the following objective function:

$$\theta = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N} \left\| \boldsymbol{x}_i - R_\theta(\boldsymbol{y}_i) \right\|^2$$

where R_θ denotes the entire convolutional neural network with parameters θ proposed to train a noise function by applying the residual learning formulation:

$$\theta = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N} \left\| R_\theta(y_i) - (y_i - x_i) \right\|^2$$

In seismic exploration, the $\boldsymbol{x}$ and $\boldsymbol{y}$ can be regarded as the true signal and original seismic data, respectively. All these CNN based denosing methods require the clean data and the corresponding noisy data in the training process. However, it is unfeasible to obtain the purely clean seismic data in practice. We proposed to minimize a new objective function by using DnCNN. Our method add white noise $\boldsymbol{n}'$ to the original seismic data $\boldsymbol{y}$ to generate the new noisy seismic data $\boldsymbol{y}'$ and the objective function is given by:

$$\theta = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N} \left\| R_\theta(y_i) - (y_i' - y_i) \right\|^2$$

$$\theta = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N} \left\| R_\theta(y_i) - n_i' \right\|^2$$

According to the statistical properties of white noise, the distribution of the original white noise $\boldsymbol{n}$ and the additive white noise $\boldsymbol{n}'$ are given by:

$$n_i \sim \chi(\mu_1, \sigma^2) \qquad n_i' \sim \chi(\mu_2, \sigma^2)$$

We can also define the Energy density of the nth original white noise E_n and additive white noise $E_{n'}$:

$$E_n = \frac{1}{N}\sum_{i}^{N}(n_i)^2 \quad E_{n'} = \frac{1}{N}\sum_{i}^{N}(n_i')^2$$

Since the Fourier spectrum of white noise is well known, and the energy density can be treated as a constant with sufficient number of trials. In this paper, the energy density can be estimated by the peak signal noise ratio (PSNR):

$$MSE = \frac{1}{N}\sum_{i}^{N}(y_i - \hat{y})^2$$

$$PSNR = \frac{\max(\boldsymbol{y}^2)}{MSE}$$

where $\hat{y}$ denotes the mean value of the original seismic data and MSE is the mean squared error. Then, we can get:

$$PSNR = \frac{E_x}{E_n} = \frac{E_y - E_n}{E_n}$$

$$E_n = \frac{E_y}{PSNR+1} = \frac{1}{PSNR+1}\frac{1}{N}\sum_{i}^{N}(y_i)^2$$

$$E_{n'} = \frac{E_{y'}}{PSNR'+1} = \frac{1}{PSNR'+1}\frac{1}{N}\sum_{i}^{N}(y_i')^2$$

where E_x and E_y denote the energy density of true signal and recorded signal, respectively. If $E_n = E_{n'}$, we can get:

$$\theta = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N} \left\| R_\theta(y_i) - n_i' \right\|^2 \approx \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N} \left\| R_\theta(y_i) - n_i \right\|^2$$

Thus, our proposed method can simulate the original noise by adding enough additive white noise and minimizing our proposed objective function.

EMD-DnCNN

The frequency spectrum of true signal and noise is band-limited, while the additive white noise meet the Gaussian distribution at full band. Thus, we proposed to first decompose the seismic data into different components by using empirical mode decomposition (EMD). Then, using the DnCNN with our proposed objective function to learn the feature of existed white noise at different frequency band.

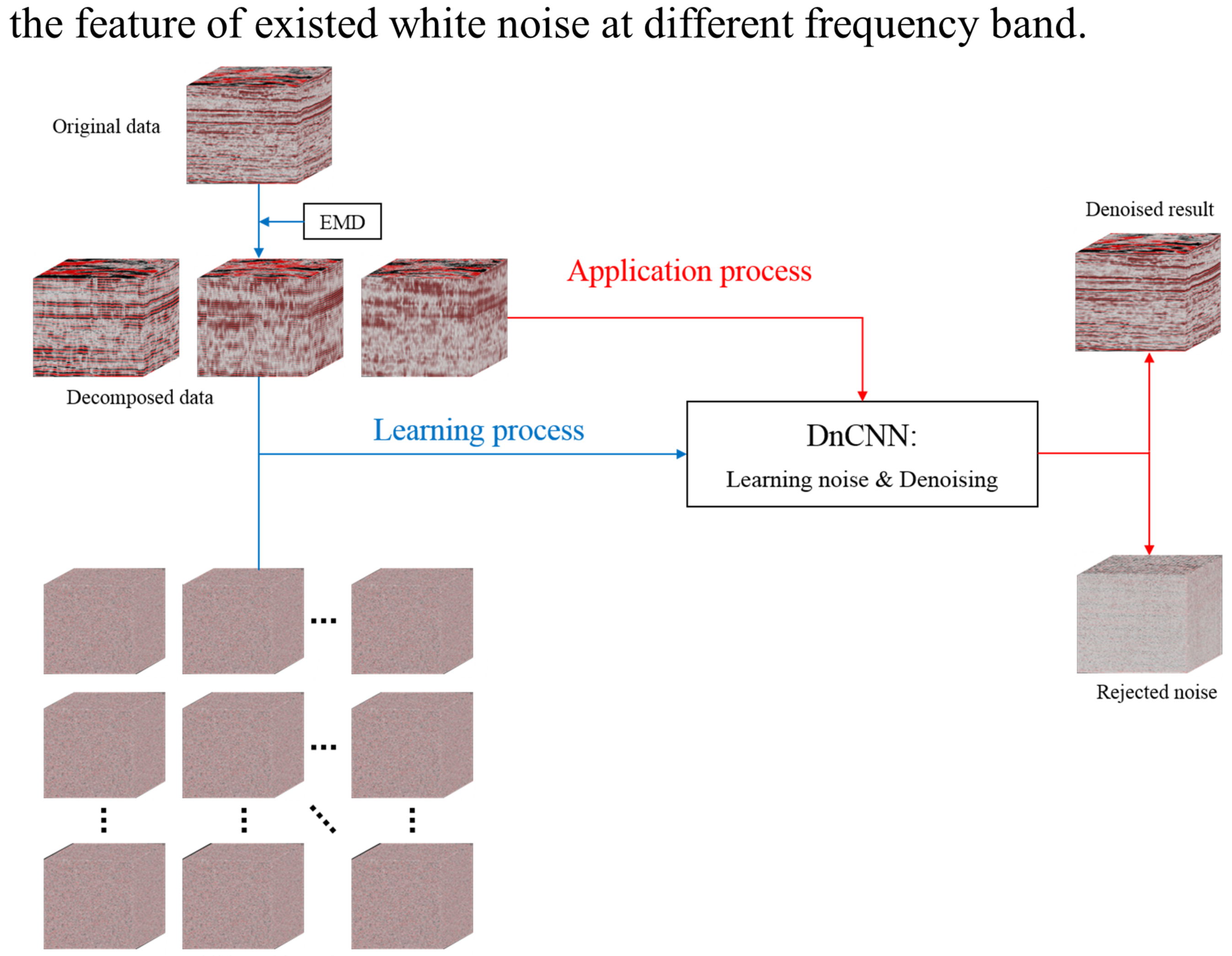

Figure 1. The workflow of our proposed method for seismic noise attenuation.

Application

We then test on a real seismic surveys to illustrate the effectiveness our proposed method and compare with the traditional method of *f-x* EMD. The seismic survey is named Penobscot and was acquired over Scotian shelf, oversea Canada. The Penobscot seismic survey contains 601 inlines and 482 crosslines. The time increment of the Penobscot seismic survey is 4ms.

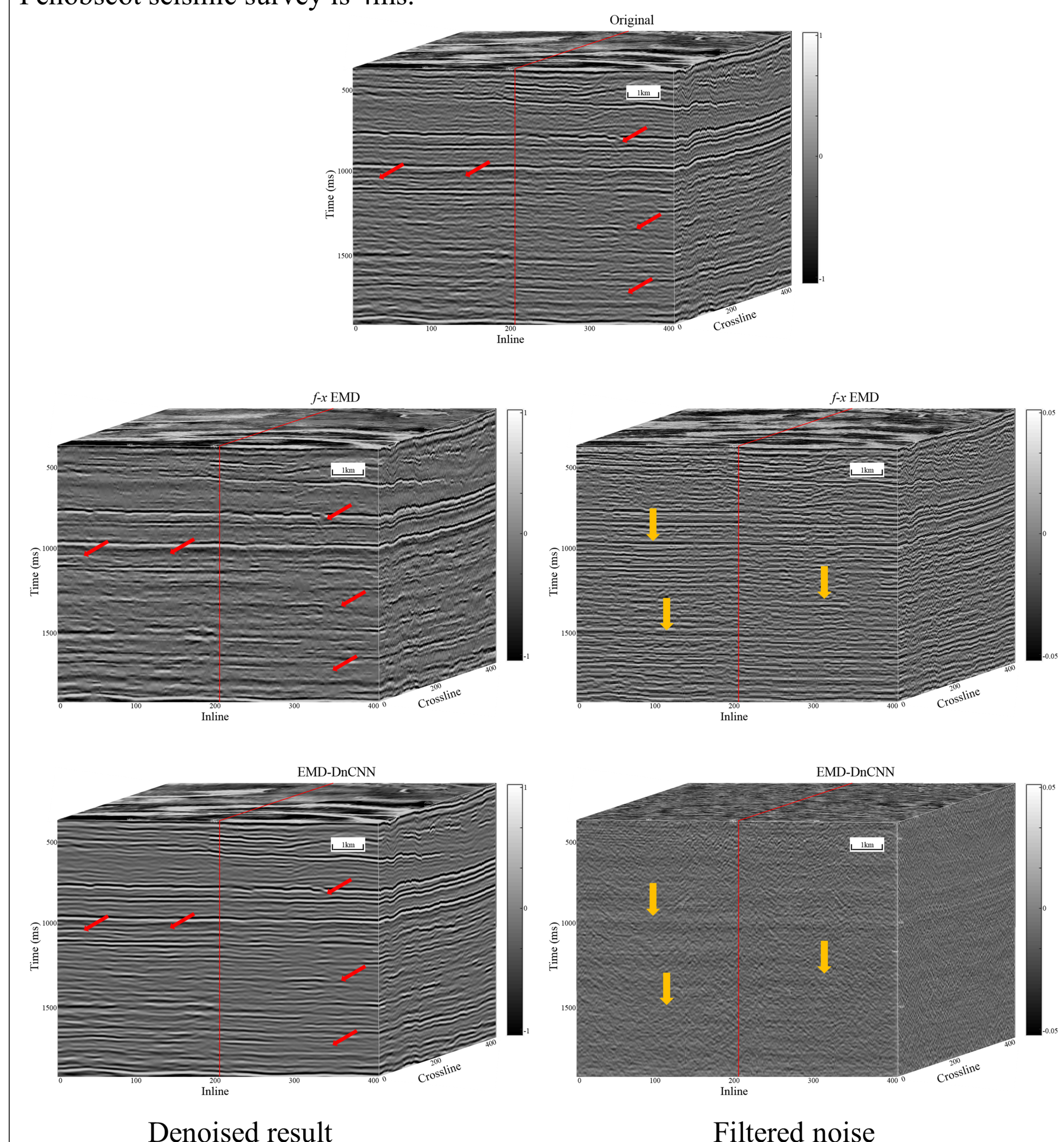

Figure 2. Illustration of the 3D volume denoised result and filtered noise on the seismic survey of Penobscot.

Conclusion

We propose a novel seismic noise attenuation method by modifying the objective function of DnCNN and integrating with the algorithm of EMD. Our proposed method that named EMD-DnCNN do not require the clean seismic data as the "label". Based on the statistical properties of white noise, we propose to use the additive white noise to simulate the feature of original white noise. Since the frequency spectrum of true signal and real white noise are band-limited. The proposed method integrated our modified DnCNN with EMD to learn the feature of original white noise at different frequency bandwidth. As a result our method obtained higher SNR at the denoised results and less visible reflectivity at filtered noise than the conventional method of *f-x* EMD. The field data example test demonstrate that our method not only properly rejects the white noise but also certain migration artifacts.