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Seismic random noise suppression using an adaptive nonlocal means algorithm*

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Abstract: Nonlocal means filtering is a noise attenuation method based on redundancies in image information. It is also a nonlocal denoising method that uses the self-similarity of an image, assuming that the valid structures of the image have a certain degree of repeatability that the random noise lacks. In this paper, we use nonlocal means filtering in seismic random noise suppression. To overcome the problems caused by expensive computational costs and improper filter parameters, this paper proposes a block-wise implementation of the nonlocal means method with adaptive filter parameter estimation. Tests with synthetic data and real 2D post-stack seismic data demonstrate that the proposed algorithm better preserves valid seismic information and has a higher accuracy when compared with traditional seismic denoising methods (e.g., f-x deconvolution), which is important for subsequent seismic processing and interpretation.
Keywords: seismic prospecting; adaptive; nonlocal means; random noise attenuation

Introduction

The expansion of seismic studies to deep layers, complex structures and lithology exploration have increased the demand for high quality seismic data. The quality of the seismic data directly affects the subsequent processing and interpretation. Improving the signal-to-noise ratio and data quality are crucial for studies that use seismic data. Many denoising methods have been proposed such as f-k filtering (Stewart and Schieck, 1993), median filtering (Bednar, 1983), f-x deconvolution (Canales, 1984), and curvelet thresholding (Neelamani et al., 2008). However, in addition to removing noise, such methods also remove some useful data components. How to protect the useful seismic information while removing noise is very important for high-resolution seismic exploration and the interpretation of seismic data.

The nonlocal means (NLM) filtering method originated in the field of image processing. Because many image denoising methods cannot retain fine structures, the NLM filtering algorithm was proposed by Buades et al. (2005). This algorithm is an innovation of the traditional local denoising model and accomplishes denoising by fully utilizing redundant information in natural images. The algorithm can retain useful image information during denoising. The NLM algorithm contains two main features: the restored value of each pixel is a weighted average of the gray values of all similar pixels

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within the image, and the similarity between different pixels is computed using the neighborhoods around the pixels (which is better than the direct measurement of the pixels themselves). Because for each pixel the algorithm computes the weighted average of all the pixels with similar gray values, the algorithm is highly redundant, which restricts its applications (Buades et al., 2005). To overcome this problem, Mahmoudi and Sapiro (2005) attempted to decrease the computational time by considering only a portion of the image for denoising, and ignored images parts with small weights. Buades et al. (2010) proposed a block-wise implementation of the nonlocal means denoising algorithm, referred to as BNLM. Wang et al. (2006) proposed an efficient algorithm based on image integration and the fast Fourier transform. Sheng et al. (2009) implemented such an algorithm on a GPU using parallel computing. The NLM denoising algorithm has been used successfully to denoise various types of data, such as MRI data (Coupé et al., 2008) and radar data (Deledalle et al., 2011). Bonar and Sacchi (2012) were the first to use NLM in seismic data processing, using the traditional NLM methods and analyzing the impact of different filter parameters. Considering the computational efficiency and the selection of filter parameters in the real data processing, we propose an adaptive filtering method based on the block-wise implementation of nonlocal means, referred to as ABNLM. Tests with synthetic and real data show that the ABNLM method can retain useful seismic information during the denoising process, eliminating the impact of improper filter parameters. Compared with f-x deconvolution, ABNLM results are more accurate. The implementation of this algorithm also lays a good foundation for its applications in large-scale seismic data processing.

Theory

NLM filtering

For each pixel x_i in the image, the value of the pixel after NLM filtering is as follows (Buades et al., 2005):

$$NL(x_i) = \sum_{x_j \in V} w(x_i, x_j) x_j, \qquad (1)$$

where V is the image and the weight $w(x_i, x_j)$ depends upon the similarity between the pixels x_i and x_j, satisfying the conditions $0 \le w(x_i, x_j) \le 1$ and $\sum_{x_j} w(x_i, x_j) = 1$. Note that the value of the pixel that is supposed to be processed is a weighted average of all pixels in the image. In order to better measure the similarity between pixels, a method utilizing their neighborhoods was introduced by Buades et al. (2005).

In the image, N_i represents the neighborhood of the pixel x_i and has an area of $(2d+1)^2$. The pixels in the neighborhood N_i are denoted x_{Ni}, where $x_{Ni} = (x_k, k \in N_i)$. Therefore, the similarity between pixels x_i and x_j depends upon the similarity of the intensity of vectors x_{Ni} and x_{Nj}. The Euclidean distance between vectors x_{Ni} and x_{Nj} is used to measure their similarity and is represented as $\|x_{Ni} - x_{Nj}\|_2^2$. Efros and Leung (1999) proved that computing the similarity of the neighborhood with Euclidean distance is an effective method. The weight can be computed using the Euclidean distance:

$$w(x_i, x_j) = \frac{1}{Z_i} \exp\left(-\frac{\left\|x_{N_i} - x_{N_j}\right\|_2^2}{h^2}\right). \qquad (2)$$

where Z_i is a normalizing factor defined by

$$Z_i = \sum_j \exp\left(-\frac{\left\|x_{N_i} - x_{N_j}\right\|_2^2}{h^2}\right)$$

and ensures that $\sum_{x_j} w(x_i, x_j) = 1$. The parameter h controls the decay of the exponential function. Studies have shown that the filter parameter h is related to the standard deviation of the image noise; when h is too large, the image will be blurred, but smaller values of h will make the denoising incomplete (Buades et al., 2008).

In the traditional NLM denoising algorithm, each pixel is denoised by computing a weighted average of all other pixels in the image. For 2D images of size T^2, the computational complexity of the denoising algorithm is about $O(T^2 * T^2 * (2d+1)^2)$, making its computational efficiency greatly reduced. This makes it difficult to conduct real-time processing of large-scale seismic data (Coupé et al., 2008). To overcome this problem, we introduce an improved denoising algorithm based on the block-wise implementation.

BNLM filtering

The BNLM filtering method can improve the computational efficiency of denoising algorithms and is composed of the three following important steps (Coupé et al., 2008):

(1) Dividing the image into overlapping blocks:

The image V is divided into small overlapping blocks

B_{ik} of area $(2a+1)^2$ centered on pixel S_{ik} so that $V = \cup B_{ik}$. The distance between different blocks is represented as n and satisfies $2a+1>n$ to ensure global continuity in the image. For simplicity, we define $n=2a-1$.

(2) NLM filtering is performed with these blocks:

For each block B_{ik}, NLM filtering is performed as follows:

$$NL(u(B_{ik})) = \sum_{B_j \in V} w(B_{ik}, B_j) u(B_j). \tag{3}$$

where

$$w(B_{ik}, B_j) = \frac{1}{Z_{ik}} \exp\left(-\frac{\|u(B_{ik}) - u(B_j)\|_2^2}{h^2}\right),$$

V represents the image, $u(B)$ represents the value of the block B, and Z_{ik} is a normalizing factor that ensures $\sum_{B_j} w(B_{ik}, B_j) = 1$.

(3) Because pixels can be included in the overlapping blocks after filtering, we can obtain more than one value for each pixel. For a given pixel, we suppose the different values are stored in the vector A and the final denoising value is the average of elements in the vector A:

$$NL(x_i) = \frac{1}{|A|} \sum_{p \in A} A(p). \tag{4}$$

In the block-wise implementation, the NLM algorithm is performed based on every block instead of each pixel. The similarity between different blocks is measured by the Euclidean distance between the blocks. Figure 1a describes the strategy of traditional NLM filtering. For denoising each individual pixel, all pixels in the image are used to calculate the necessary weights. The similarity is computed through their neighborhood and the restored value is the weighted average of these pixels. Figure 1b describes the strategy of BNLM filtering. NLM filtering is performed based on every block, and the similarity is measured between the blocks. Weighted averages are computed for each individual block. The computational complexity decreases when the BLNM filtering algorithm is used. The complexity for an image of size T^2 is about $O((2a+1)^2 * T^2 * (T/n)^2)$. For example, when a = d, the complexity is divided by n^2, which improves the computational efficiency and reduces the computational burden.

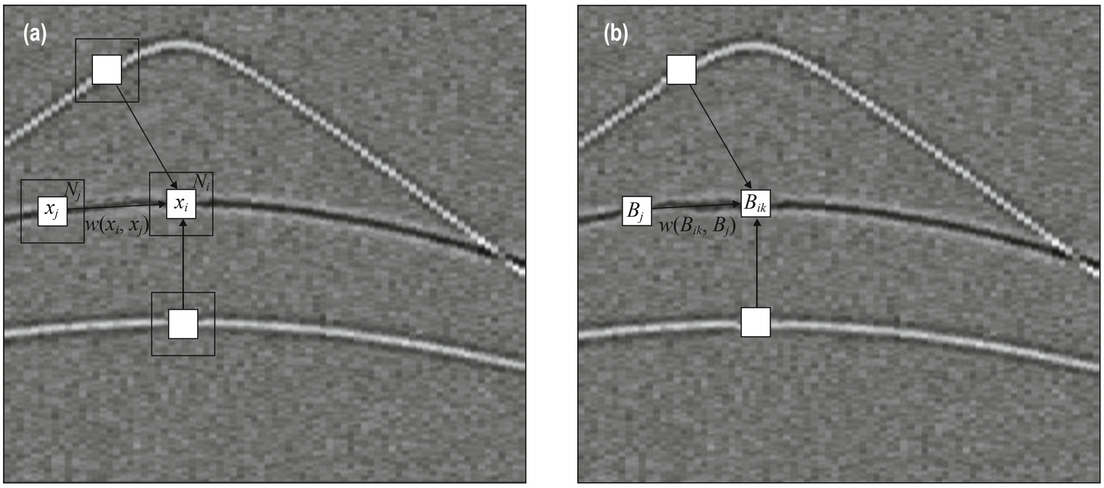


Fig.1 The strategy of traditional NLM filtering (a)and the strategy of BLNM filtering (b).

Adaptive filter parameter

The NLM denoising algorithm results are largely influenced by the selection of the filter parameter h. If the parameter is too big, then the details and edge information will be lost while denoising, making the image blurred. If the parameter is too small, then the noise cannot be completely suppressed. Experiments show that for the BNLM algorithm, the optimal filter parameter is approximately the standard deviation of the image noise (Manjón et al., 2010). Therefore, we can estimate the filter parameter by estimating the standard deviation of the image noise.

Suppose that the noise standard deviation of an image is represented as σ, then:

$$d(B_i, B_j) = E\|u(B_i) - u(B_j)\|_2^2 = \|u_0(B_i) - u_0(B_j)\|_2^2 + 2\sigma^2. \tag{5}$$

where u is the image with noise and u_0 is the noise free image. If B_i=B_j, then $d(B_i$=$B_j)$ = $2\sigma^2$. If we assume that the block B_i has at least one block equal to itself, B_j, then:

$$\sigma^2 \approx \min(d(B_i, B_j))/2, \forall j \neq i. \quad (6)$$

Using this formulation, we can obtain the optimal filter parameter h by estimating the noise standard deviation.

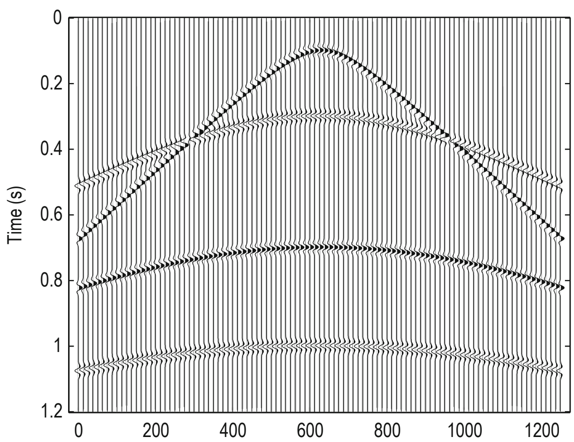
Experimental analysis

We introduce nonlocal image processing into seismic denoising. The seismic data satisfies the NLM assumption of NLM that the valid information has a certain redundancy. This phenomenon exits in most data or images. We treat the seismic cross section as a gray image. The intensity of each pixel is between 0 and 255 and is related to the amplitude of the different sampling points. Because the amplitude of the seismic data is not always positive, it is necessary to deduct the minimum value of the seismic data before this method is performed to ensure the amplitude is not negative. Then, the data can be treated as a 2D gray image, and the value of each sampling point is equivalent to the pixel intensity and ranges from 0 to 255. Using this nonlocal averaging technique, the restored value plus the minimum values is the final denoising result for each pixel.

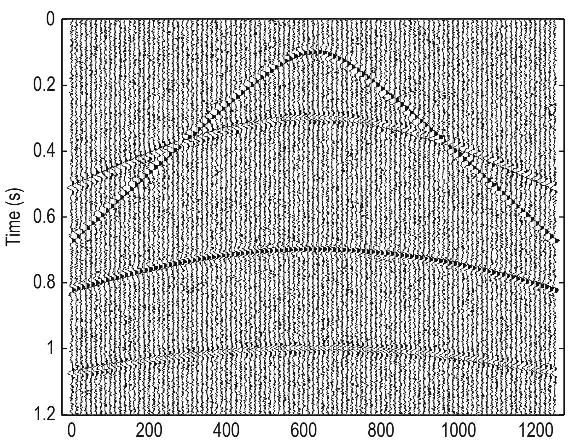
In order to demonstrate the effectiveness of this method in seismic processing, tests on synthetic and real data are performed. We define the signal-to-noise ratio (SNR) as SNR = $20\log10\|m0\|_2/\|m-m0\|_2$, where $m0$ is the noise free data and m is the denoising result.

Experiments on synthetic data

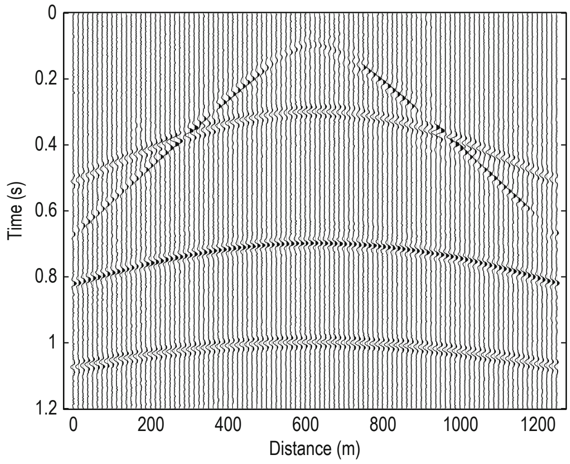
For synthetic seismic data without noise, the time sampling interval is 2 ms and the number of traces is 101 (Figure 2a). We add Gaussian white noise to the seismic data (Figure 2b). The SNR is 7.56 and the noise standard deviation is 0.0304. Figure 2c shows the denoising result after f-x deconvolution using a sliding 30×15 window in the time and space directions. The SNR after f-x deconvolution is 10.94. Although the noise is suppressed to a certain extent, the useful information is also destroyed, especially at the top of hyperbola located at about 0.2 s. Figure 3a shows the difference between the f-x denoising result (Figure 2c) and the noise free data (Figure 2a). There is a large number of valid information residuals in the range of 0.2–0.8 s that make the denoising result not conducive to the subsequent processing. Figure 2d is the denoising result after BLNM filtering (a = 3, h = 0.0102). The SNR after BLNM filtering is 14.64; the noise is suppressed and the SNR is improved compared to the f-x deconvolution results. From the difference (Figure 3b) between the denoising result (figure 2d) and the noise free data (Figure 2a), we can see that there is almost no useful signal, however, the noise is not suppressed clearly because of the small filter parameter. Figure 2e is the denoising result from BLNM filtering (a = 3, h = 0.1824). The result has an SNR of 13.30 and the filter parameter is obviously too large. The noise is suppressed better compare with Figure 2d, and the denoising result should be more clear. However, the energy of the useful information is weakened compared with the noise free data (Figure 2a). Figure 3c is the difference between this denoising result (Figure 2e) and the noise free data, from which we can see that although the noise is suppressed well, the valid signal is weaken because of the big filter parameter. Figure 2f is the denoising result from ABLNM filtering (a = 3); the SNR is 21.57 and the random noise is suppressed very well. The denoising result is very clear and the valid signal



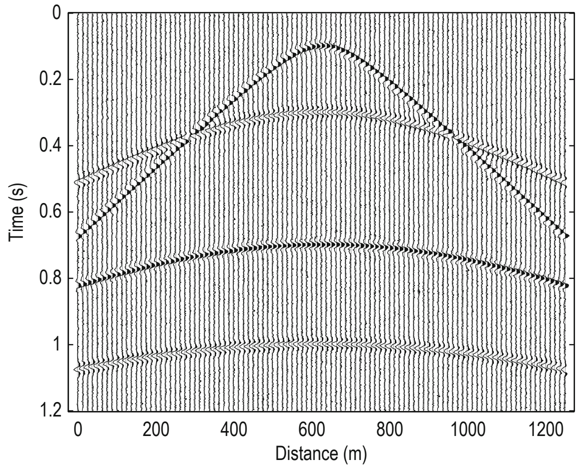
(a) Synthetic seismic data without noise.



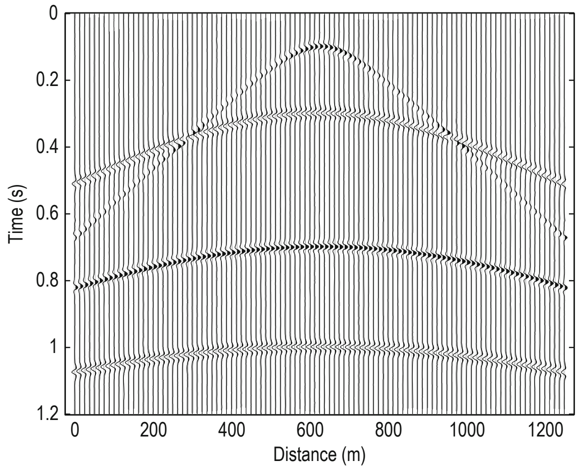
(b) Synthetic seismic data contaminated with noise, SNR=7.56.



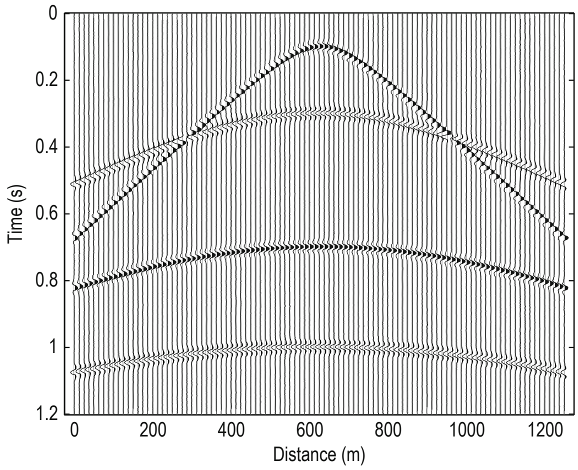
(c) F-x deconvolution denoising result, SNR=10.94.



(d) BLNM denoising result with small filter parameter, SNR=14.64.



(e) BLNM denoising result with big filter parameter, SNR=13.30.

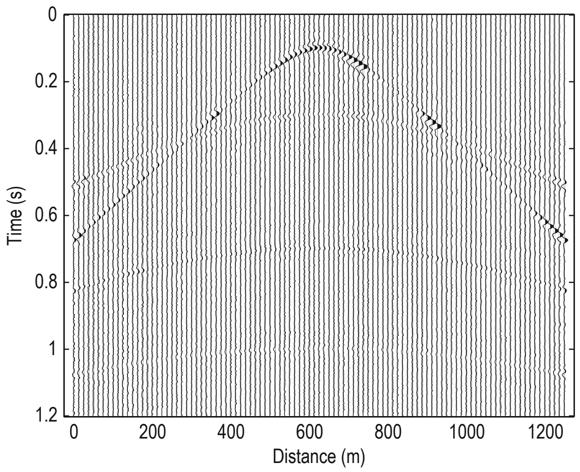


(f) ABLNM denoising result, SNR=21.57.

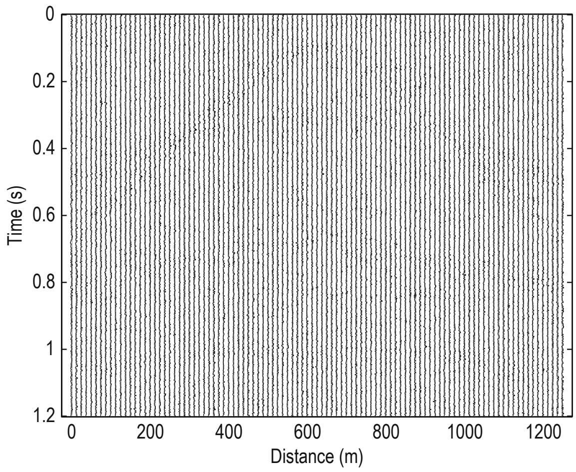
Fig.2 Different denoising results of the synthetic seismic data.

is distinct. Figure 3d shows the difference between the denoising result and the noise free data; there is almost no useful information and this denoising method overcomes the impacts of improper filter parameter and the valid signal is not destroyed. Compared with the f-x deconvolution method, this method better protects the useful information.

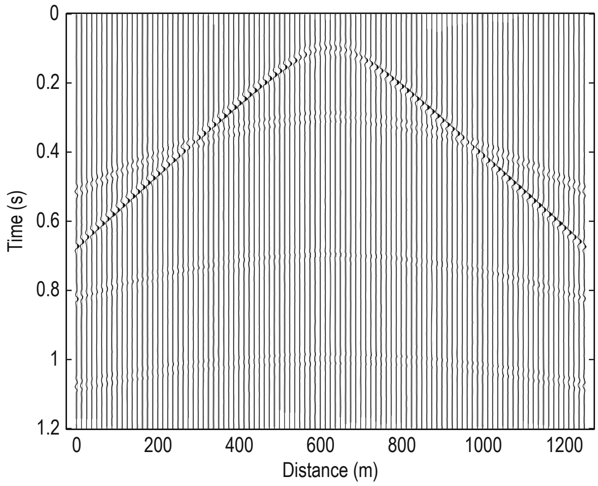
The differences between the denoising results from different methods and the noise free data are shown in Figure 3.



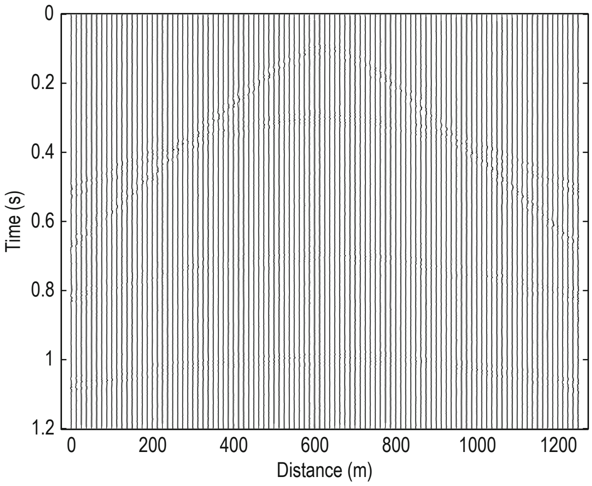
(a) By f-x deconvolution.



(b) By BLNM with a small filter parameter.



(c) By BLNM with large filter parameter.

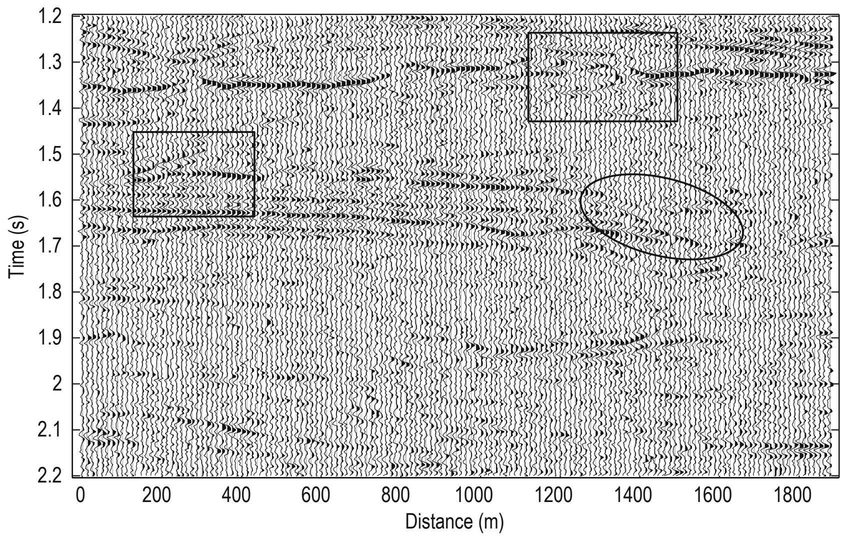


(d) By ABLNM.

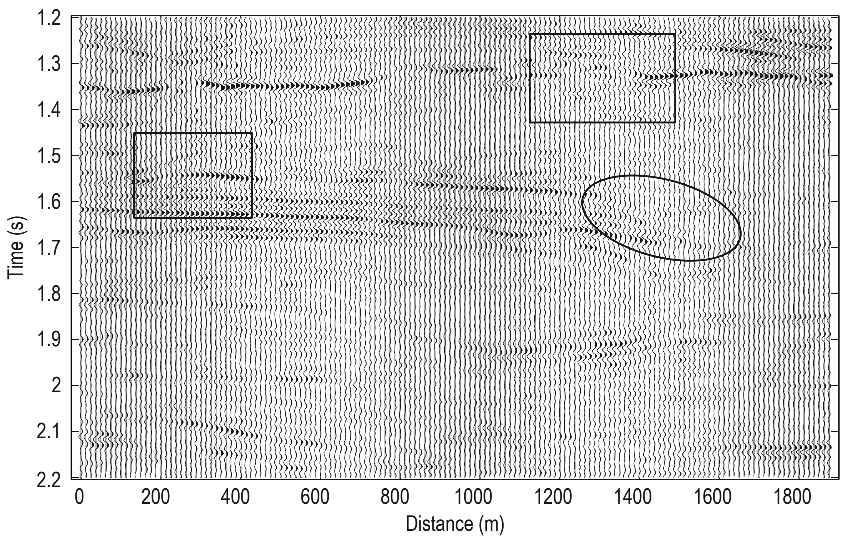
Fig.3 Difference profiles for different methods.

Experiments on real data

A section of the real 2D post-stack seismic data from land has a time sampling interval of 4 ms, trace interval of 12.5 m, a time range of 1.2–2.2 s, and 151 traces (Figure 4a). There are many discontinuous and unstable seismic events in this seismic section, the valid information and these seismic events become blurred because of noise, we use f-x deconvolution and ABLNM (a = 5) to remove the noise. Figure 4b is the denoising result from f-x deconvolution with a 25×15 window along the time and space directions. The post-filtering result is more clear but the valid signal is also destroyed during noise removing, especially the fluctuant and discontinuous events delineated by the squares located at 1.3 s and 1.5 s and the tips of seismic events delineated by the ellipse located at about 1.6 s. We can use sliding windows in the f-x deconvolution to overcome the errors from nonlinear events, however, the error correction is limited. From the section showing noises removed using f-x deconvolution (Figure 4d), we see that there is some valid information residuals, implying that useful information is also reduced during noise removal that is not conducive



(a) Original post-stack seismic data.



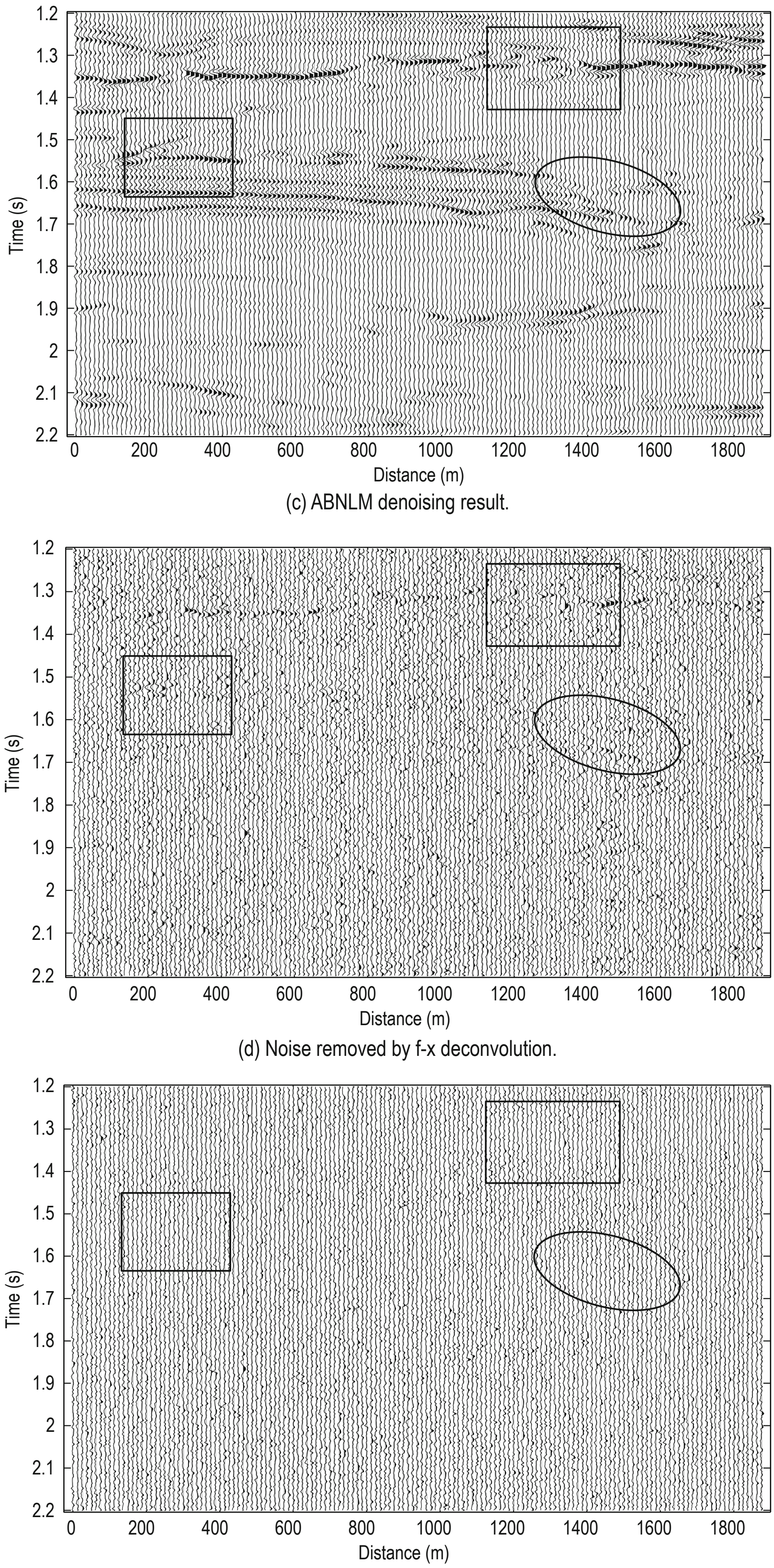
(b) F-x deconvolution denoising result.

to the subsequent processing. Figure 4c shows the denoising result from ABLNM; this result seems better and the useful information is prominent compared with the f-x deconvolution denoising result, and the complex structures and the discontinuous layers are also protected. Figure 4e shows the noise removed using ABLNM method; there is nearly no valid information residuals, showing that the useful information is not lost during noise removal, which is very important for further processing and interpretation.

Conclusions

The ABNLM is a denoising method based on the idea that any image has redundancy. It is composed of BNLM filtering and adaptive filter parameter estimation, overcoming problems resulting from computational burdens and improper filter parameters. The method performs well in seismic data processing, and we obtained the following conclusions: (1) This paper uses a nonlocal idea, which was originally developed for image processing, in seismic denoising. The method assumes that the valid information repeated in the image or data is distributed in the whole space instead of a limited region around the pixel, making the process nonlocal. The restored value of the pixel is the weighted average of all pixels in image. Based on the redundancy property of seismic data and the block-wise implementation, we consider the seismic data as an image, allowing us to construct a simple algorithm that can protect the valid signal during denoising. Experiments show that a trade-off between denoising and protecting the useful information can be achieved.

(2) The ABNLM filtering corrects problems resulting from improper



(c) ABNLM denoising result.

(d) Noise removed by f-x deconvolution.

(e) Noise removed by ABNLM.

Fig.4 Real seismic data denoising results.

filter parameters in traditional NLM filtering, and the numerical results describe its advantage. Experiments on real seismic data show that this method outperforms traditional denoising methods (e.g., f-x deconvolution), protecting the valid seismic events during denoising, especially for complex and discontinuous layers.(3) The seismic data is divided into blocks when ABNLM filtering is performed. The block size should be chosen so it is large enough to contain the seismic signal information, and it should be larger than or equal to the seismic data wavelet length. The influence of block size and overlapping size on the denoising result and computational efficiency will be discussed in further research.

(4) The NLM algorithm can be easily implemented in parallel processes. Using a parallel implementation and a fast algorithm, this method can be extended into three-dimensional space or higher, providing support for the 3D pre-stack or post-stack seismic data denoising.

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