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Seismic data random noise attenuation using DBM filtering

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ABSTRACT Seismic random noise attenuation is a very important step in seismic processing, resulting in seismic interpretation enhancement. Decision-based median (DBM) filtering is proposed here for seismic random noise attenuation to improve the signal to noise ratio (S/N) and the quality of the seismic images. Unlike conventional median filtering, where both the signal and noise samples are affected, a DBM filter predominantly affects the noise samples using a selection criterion based on a threshold. In other words, using a DBM filter, noise samples are initially detected, and then the filtering operation is applied to them. When the DBM filter is applied to the synthetic and observed pre/post stack seismic data sets, its superiority over the conventional median filter in suppressing random noise and improving S/N of seismic data is demonstrated.

Key words: seismic data, DBM filter, median filter, random noise, denoising.

1. Introduction

Removing noise from seismic data is a challenging research field in seismic data processing. The quality of seismic images is improved by random noise attenuation; hence, interpretation of seismic events is greatly facilitated. Random noise filtering increases the general interpretability of seismic data and also improves the performance of automatic horizon picking.

Various methods have been introduced over the years for suppressing the random noise in seismic data. For high noise levels, f-x deconvolution technique based on signal predictability (Canales, 1984) is an effective method (Spitz and Deschizeaux, 1994). Singular value decomposition (SVD) methods (Lu, 2006) decompose the signal and noise into different subspaces and can be used globally or locally (Bekara and Baan, 2007) to suppress random seismic noise. Wavelet (Donoho *et al.*, 1996) and curvelet transforms (Starck *et al.*, 2002) were also successfully employed for random noise attenuation.

The median filter is a simple and robust filter which is widely used due to its good noise-suppressing power and computational efficiency (Bednar, 1983). Different types of median filters have been developed, including stack filters, multistage median (Liu *et al.*, 2006), relaxed median (Hamza and Krim, 2001), rank conditioned rank selection, and weighted median (Vijay Kumar *et al.*, 2007). Liu *et al.* (2009) presented a 1-D time-varying median filter for spike-like noise elimination in seismic data.

In this paper, we propose to use a decision method to detect noise prior to application of the median filter. This method is able to diminish the random noise while preserving the signal samples. DM is simple, effective, and could easily be implemented. In the following sections, the principles of the conventional median and decision-based median (DBM) filters are explained. Applying the suggested technique to the synthetic and observed pre/post stack seismic data, the technique's performance for seismic random noise attenuation is discussed.

2. Methodology

2.1. Median filter

Popular median filters were developed as a means of smoothing data (Tukey, 1977) in which the signal contains abrupt discontinuities. The term "median" is used here in its correct statistical sense and should not be confused with the terms mean, average value, or weighted mean. If N statistical data samples are arranged in ascending order of magnitude, then the median value is the sample in the $(N+1)/2$ position of the sequence. When N is odd, the median is the middle value of the ordered set of data. If N is even, the median is usually defined as the mean of the two middle terms of the monotonically increasing sequence. Despite changing some characteristics of an image or seismogram, noise will be significantly suppressed by median filtering.

Let $X1, X2, X3, X4, X5$ represent a sequence of statistical samples having variable magnitudes. Reordering these values so that they successively increase in magnitude will generally create a different sequence, which might for example be $X3, X5, X2, X4,$ and $X1$. The median value of this reordered sequence is $X2$. In this instance, the action of a median filter is represented in Fig. 1.

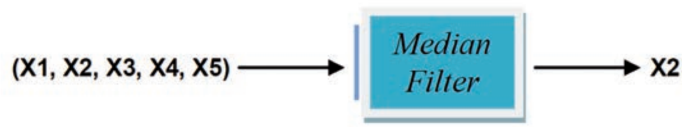

Fig. 1 - Action of the median filter.

This example illustrates the non-linear nature of the median filter (Arce, 1998). Significant developments of the median filter, such as the adaptive median filter (Lukac and Smolka, 2003), weighted median filter (Weng *et al*., 2007), and recursive weighted median filter (Arce, 2005) have been reported.

When the noise level is high, the filter will smear the details and edges and may not remove noise. To cover this deficiency, noisy pixels (seismic samples) should first be recognized and then replaced by the filter operator, while other pixels are kept unchanged. Following this notion, noise-detection techniques such as decision-based method (Cai *et al*., 2010) and switching filter (Pandey, 2008) have been introduced.

2.2. DBM Filter

To provide a trade-off between the identity filter and the median filter, the suggested method DBM is designed with a significantly simple noise - detecting method (DM). The idea behind the proposed filter algorithm is to design a filter in such a way that the identity operator acts on the noise-free samples, while the noisy pixels are affected by the filter operation (Arastehfar *et al*., 2013).

To implement the DBM filter, an image [seismic data (I)] is supposed as a vector (V) made by the rows of the image. In the vector scheme, a column vector V is built by the rows of matrix I as shown in Eqs. 1 and 2. It should be noted that the first row, the last row, the first column, and the last column are eliminated with this stratagem. So, an image $I_{n\times m}$ of size n×m becomes a vector $V_{N\times 1}$ of size N×1 in the vector outline (Eq. 2), where $N = (n-2) \times (m-2)$.

$$I = \begin{pmatrix} I_{11} & I_{12} & . & . & I_{1(m-1)} & I_{1m} \\ I_{21} & I_{22} & I_{23} & . & I_{2(m-1)} & I_{2m} \\ . & I_{32} & . & . & . & . \\ . & . & . & . & . & . \\ I_{(n-1)1} & I_{(n-1)2} & . & . & I_{(n-1)(m-1)} & I_{(n-1)(m)} \\ I_{n1} & I_{n2} & . & . & I_{n(m-1)} & I_{nm} \end{pmatrix} \tag{1}$$

$$V = \begin{pmatrix} V_{11} \\ V_{21} \\ . \\ . \\ . \\ . \\ . \\ V_{N1} \end{pmatrix} = \begin{pmatrix} I_{22} \\ I_{23} \\ . \\ I_{2(m-1)} \\ I_{32} \\ . \\ . \\ I_{(n-1)(m-1)} \end{pmatrix} \quad \text{where} \quad N = (n-2)(m-2). \tag{2}$$

$W_q(p)$ is defined as a two-dimensional processing window of size $q\times q$, where q is an odd integer and p is the central pixel within the window (Rutuja Kulkarni and Bhaskar, 2013). For example, W_3 is a filtering window with size 3×3, containing 9 pixels:

$$W_3 = \begin{pmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & p & W_{23} \\ W_{31} & W_{32} & W_{33} \end{pmatrix} \tag{3}$$

In the DM technique, noisy pixels are detected by comparing each pixel in the image with its surrounding pixels. The difference between two successive pixels in V is compared with a threshold d. The value of threshold d is not fixed and can be changed according to the noise level of data and the *'Step'* parameter. The parameter *'Step'* is a predefined value, added to d depending on the condition $|v_{i-1}-v_i|>d$, where $|\cdot|$ indicates the absolute operator and v_i denotes the i^{th} component of V.

- Threshold = d
- If $|v_{i-1}-v_i|>d$ $\{v_i = \text{median}\,(W_3(v_i)),\ d = d + Step\}$
- Else $\{d = \text{Threshold}\}$

When the noise level is low, the possibility of detecting a noisy pixel is very low. Then, providing that a pixel is detected as a noisy pixel, the condition for detecting the next pixel as a noisy one gets harder by increasing d. Otherwise, the parameter d is changed to the pre-defined value of threshold. The parameter *'Step'* has a very important role in accurate identification of noisy pixels (samples) and in preserving edges.

Thus, this is an adaptive median filter that determines which pixels in an image have been affected by noise. According to this algorithm, if the difference between two successive pixels

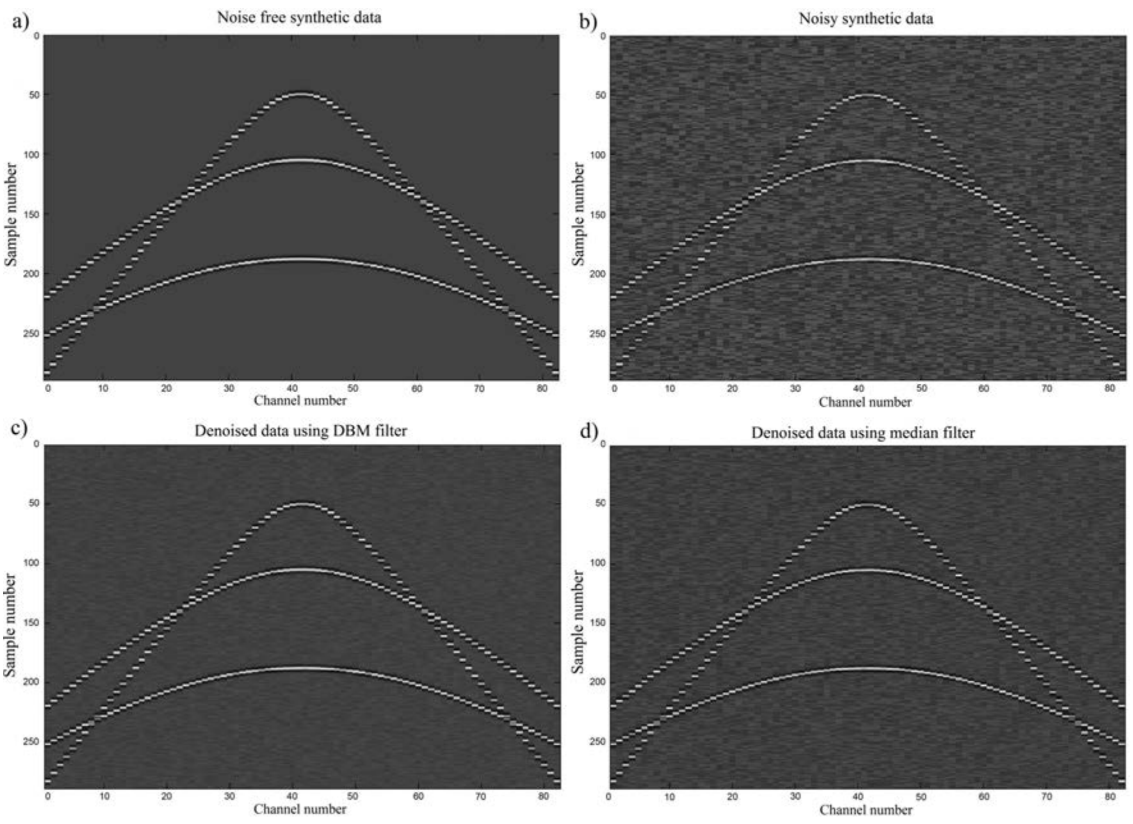

Fig. 2 - a) Noise-free synthetic data. b) Noisy synthetic data with S/N of 2, reflection events are affected by random noise. c) Denoised synthetic data using DBM filter. d) Denoised synthetic data using conventional median filter. It is clear that the DBM filter is more successful in removing random noise and increasing S/N compared to the conventional median filter.

is greater than the threshold d, the pixel is noisy and the median operation must be applied. It means that the noisy pixel will be replaced by the median value of the pixels in its neighborhood while leaving all the other pixels unchanged. If the condition $|v_{i-1}-v_i|>d$ is not satisfied, the pixel is not noisy and the identity filter will be applied.

3. Examples

3.1. Synthetic data

To prepare the synthetic model, a 30-Hz Ricker wavelet and sampling interval of 4 ms were used. The created noise-free data consists of three reflectors with t_0 200, 450, 800 ms and velocity 1000, 2200, 2500 m/s, respectively (Fig. 2a). The synthetic data include 82 traces with 284 samples per trace. Noisy data with S/N of 2 is created by adding Gaussian noise to noise-free data (Fig. 2b). From Fig. 2b, it is clear that reflection events are affected by random noise and the S/N is reduced. To implement the DBM filter, the window size is fixed at 3×3. The threshold d is set to 95 and the parameter '*Step'* is set to 5 as the optimum values. The denoised data after DBM filtering is shown in Fig. 2c. For comparison, the result of conventional median filtering is shown in Fig. 2d. Figs. 2c and 2d indicate that the DBM filter is more successful in removing random noise and increasing S/N compared to the conventional median filter.

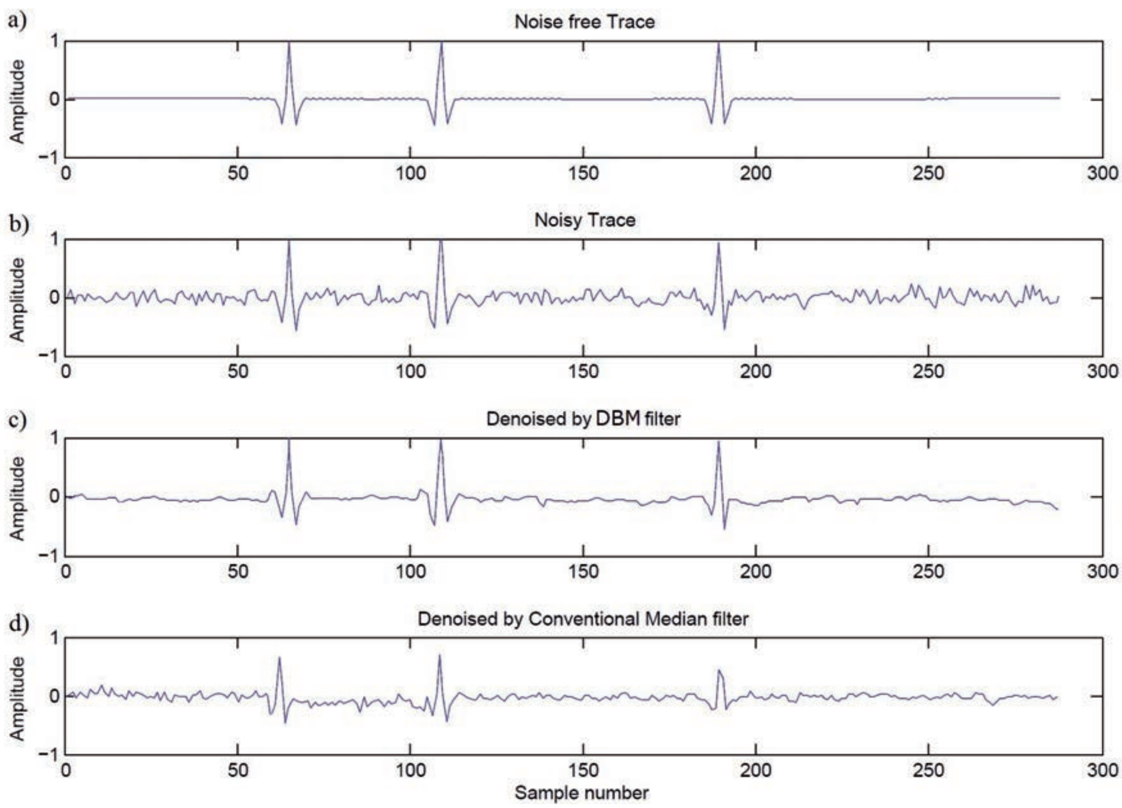

Fig. 3 - The trace number 35 selected from Fig. 2: a) noise free trace; b) noisy trace; c) denoised trace using DBM filter; d) denoised trace using conventional median filter. Comparing Figs. 3c and 3d shows the higher power of the DBM filter in comparison to the conventional median filter for random noise attenuation.

The trace number 35 from noise-free data, noisy data, and denoised data using DBM filter and conventional median filter are shown in Fig. 3, where the noise level of denoised trace using DBM filtering is decreased more than with conventional median filtering. These results demonstrate the power of the DBM filter for random noise attenuation.

To better check the performance of this technique, the residual noise is calculated. The residual noise is determined by computing the difference between noise-free traces and denoised traces. Fig. 4 indicates the residual noise in frequency domain (amplitude spectrum). It is clear that the amplitude spectrum related to DBM filtering is close to zero in all frequencies, demonstrating that random noise is greatly suppressed, while the frequency range of information (lower frequencies) is not affected considerably. However, a high level of noise still remains after the application of the conventional median filter. Spectral analysis of the residual noise confirms, therefore, the higher performance of the DBM filter in noise attenuation compared to the conventional median filter.

3.2. The real data

A real shot gather and a seismic section are also selected to further study the performance of the proposed method. The shot gather with a trace spacing of 25 m and a sample rate of 4 ms after suppressing ground roll is shown in Fig. 5a. Random noise is evident in most parts of the shot gather. In this case, for implementation of the DBM filter, the window size is fixed at 5×5. The threshold *d* is set to 80 and the parameter '*Step*' is set to 10 as the optimum values. Comparing the application of DBM and conventional median filtering in Figs. 5b and 5c, it is observed that random noise is suppressed significantly by the DBM filter, while the conventional median filter is not as effective.

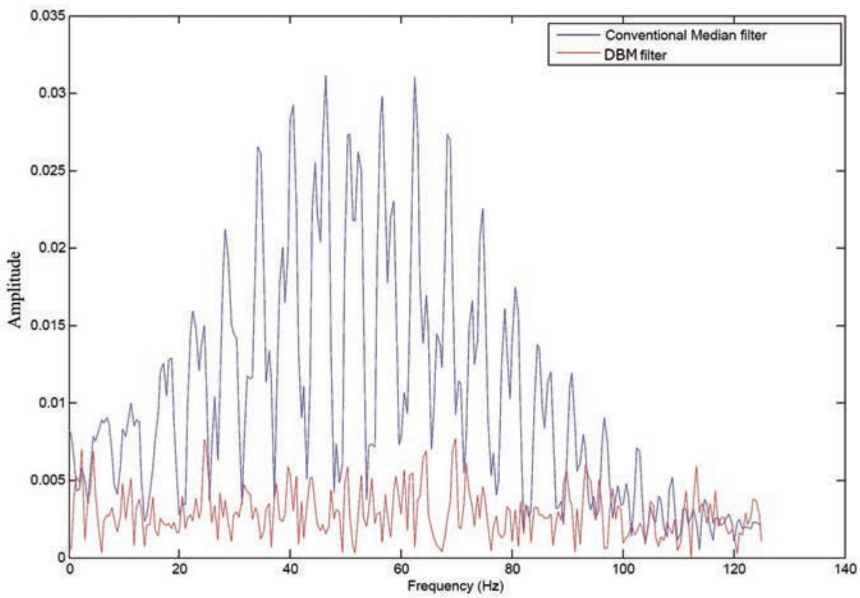

Fig. 4 - Amplitude spectrum of residual noise related to DBM (shown in red) and conventional median filtering (blue). Amplitude spectrum related to DBM filtering is close to zero in all frequencies and demonstrates that random noise is greatly suppressed. A high level of noise still remains after the application of conventional median filtering (blue).

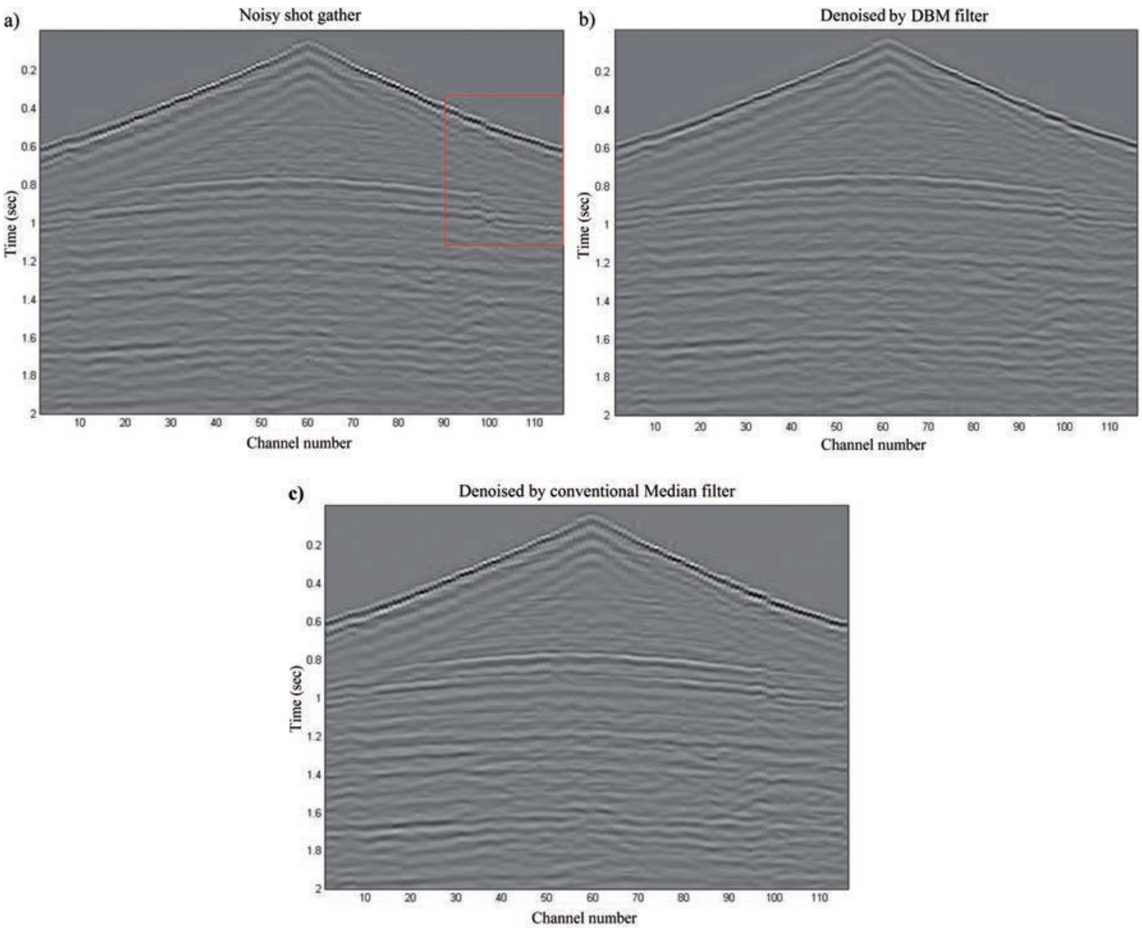

Fig. 5 - a) A shot gather with a trace spacing of 25 m and a sample rate of 4 ms. After suppressing the ground roll, the random noise is observable in most parts the data. b) The shot gather after denoising using DBM filter, random noise is suppressed significantly. c) The shot gather after denoising using conventional median filter. Results show that DBM filtering is more powerful for random noise attenuation.

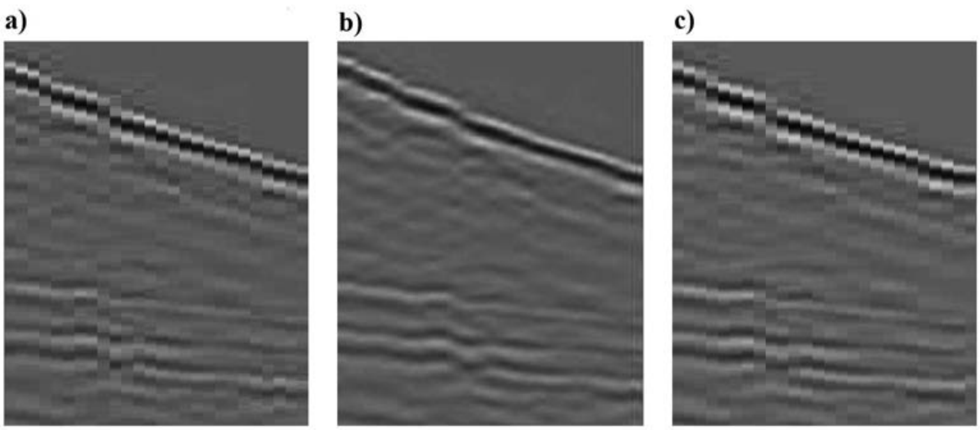

Fig. 6 - a) A zoom of a part of the shot gather in Fig. 5 (red box) before denoising. b) A selected part of the shot gather after denoising using DBM filter. c) Selected part of the shot gather after denoising using conventional median filter. From Figs. 6b and 6c, the DBM filter has effectively succeeded at eliminating the random noise.

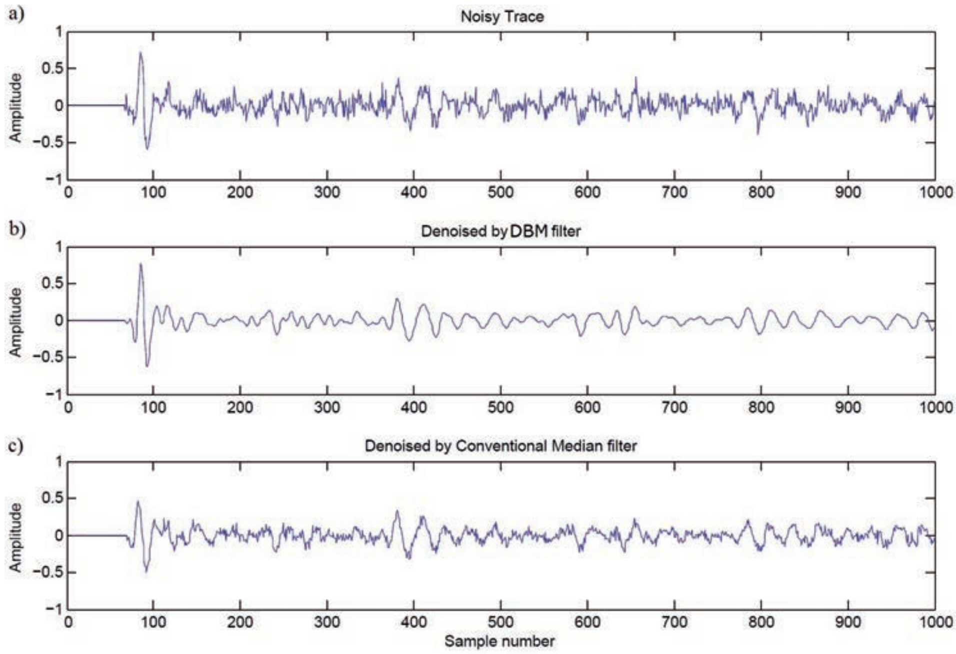

Fig. 7 - a) Trace number 50 before denoising. b) Trace number 50 after denoising using DBM filter. c) Trace number 50 after denoising using conventional median filter. Random noise is well attenuated using DBM filter, while conventional median filtering is not successful.

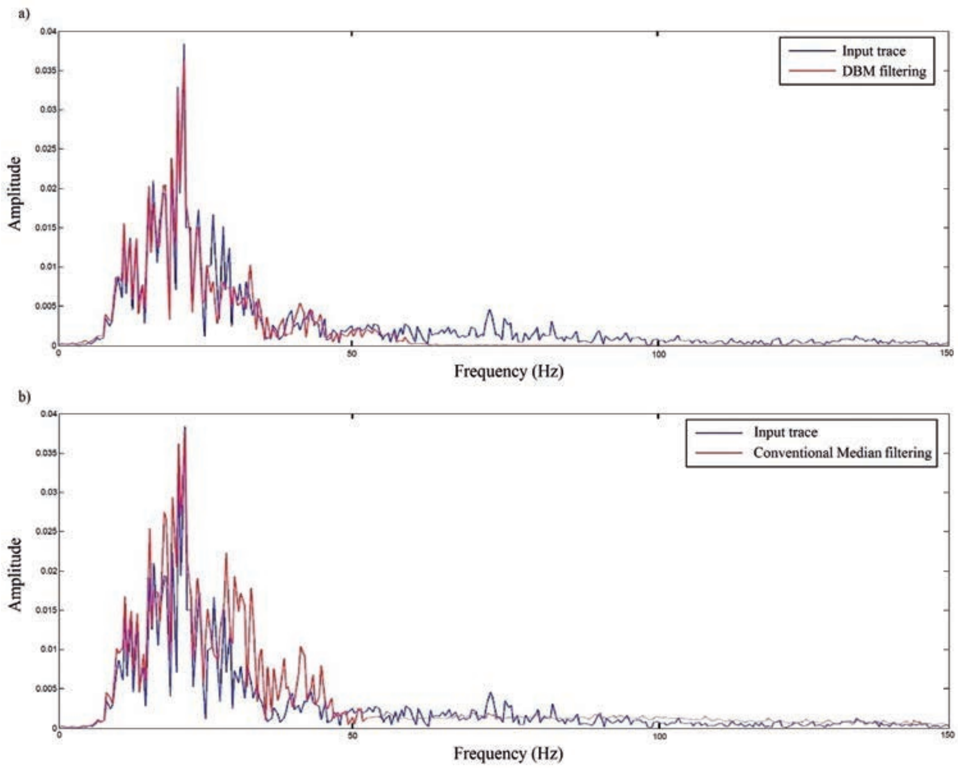

Fig. 8 - a) Amplitude spectrum of trace number 50 before and after denoising using DBM filter. b) Amplitude spectrum of trace number 50 before and after denoising using conventional median filter.

The shot gather within the red box before and after denoising using DBM and conventional median filter is shown in Fig. 6. According to Fig. 6, the random noise is attenuated and the S/N is improved greatly using the DBM filter in comparison to a conventional median filter (Figs. 6b and 6c).

To evaluate the results better, trace number 50 is selected from the shot gather in Fig. 5. This trace, before and after denoising using DBM filtering and conventional median filtering, is plotted in Fig. 7. Fig. 7b shows that the random noise is well attenuated and S/N is improved using DBM filtering, while conventional median filtering is not successful (Fig. 7c).

The amplitude spectrum of trace number 50 before and after denoising using DBM and conventional median filters is calculated and put together in Fig. 8. Comparing plots in Fig. 8a

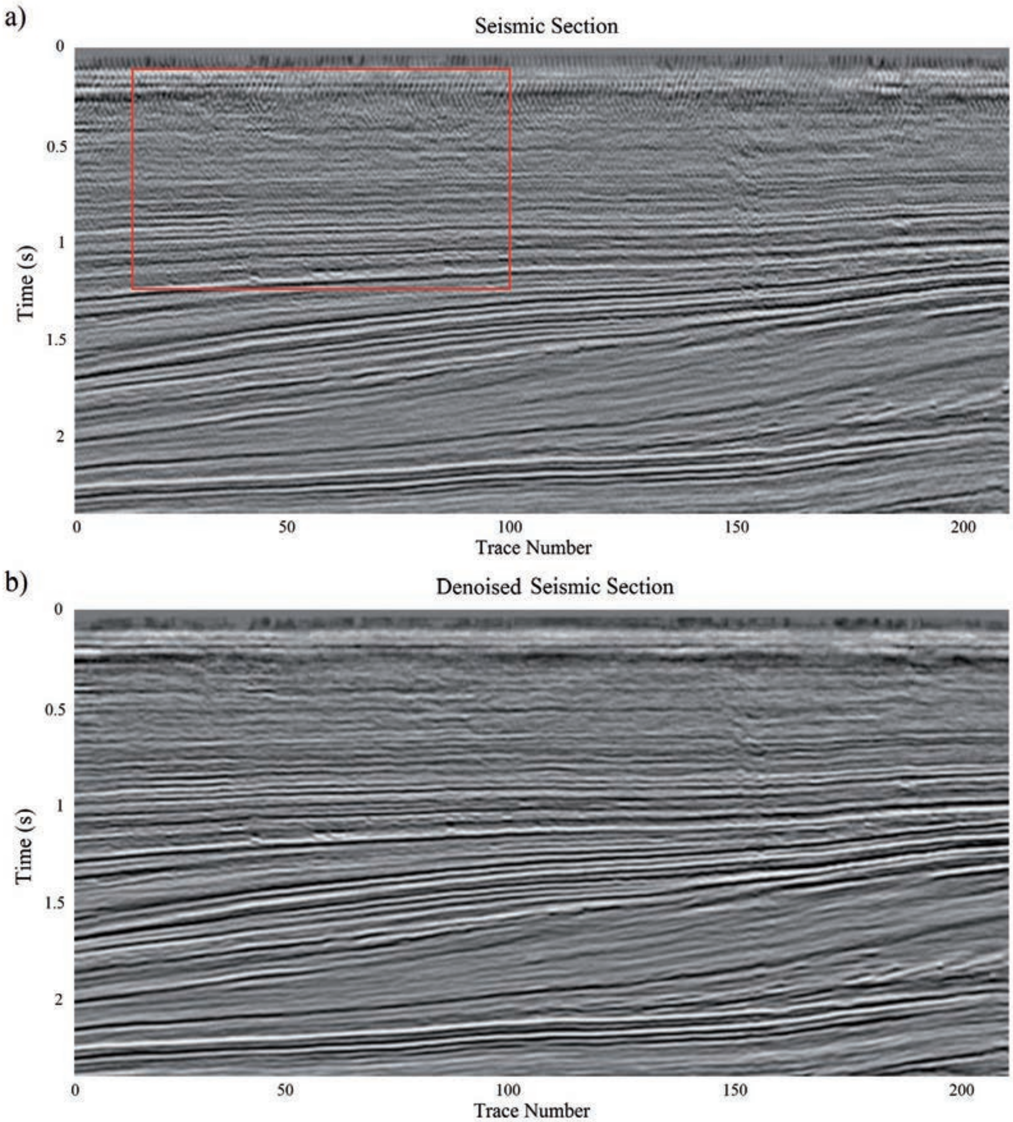

Fig. 9 - a) A noisy seismic section with 2 ms sampling interval and trace spacing of 50 m, different horizons are affected by random noise, in shallow parts particularly. b) Denoised seismic section using DBM filter, random noise is attenuated and the S/N is improved.

indicates that DBM filtering is able to significantly attenuate high-frequency components that are due, generally, to random noise, while the frequency range of information is not affected considerably. Instead, Fig. 8b indicates that the frequency range of information is affected during denoising by conventional median filtering, which is an enormous deficiency.

Another data set is a seismic section with 2 ms sampling interval and trace spacing of 50 m where horizons particularly in shallow intervals are masked and affected by random noise (see Fig. 9a). The denoised seismic section using the DBM filter is shown in Fig. 9b. To better demonstrate the results, a close-up of a part of the section (red box) before and after denoising is shown in Fig. 10. According to Fig. 10, the random noise is attenuated and the S/N is improved. Also, the lateral continuity of events is increased, and hence the interpretability of data is enhanced considerably.

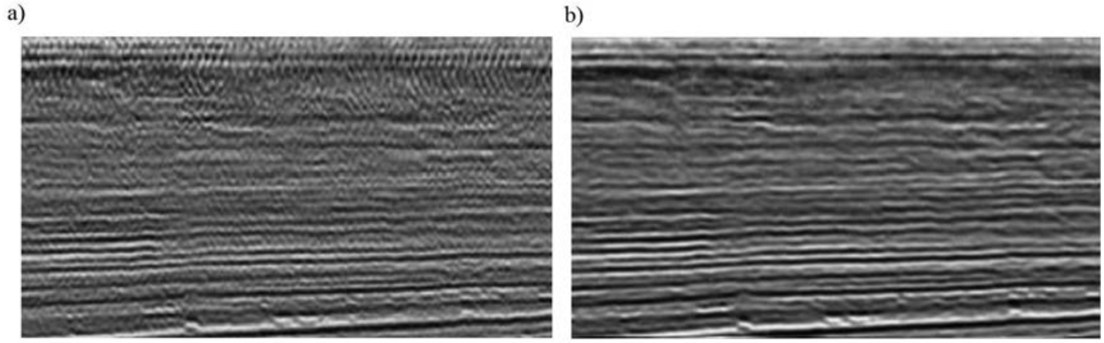

Fig. 10 - a) A zoom of a part of the section in Fig. 9 (red box) before denoising. b) A selected part of the section after denoising using DBM filter. The lateral continuity of events is increased greatly, and hence the interpretability of data is enhanced considerably.

4. Conclusion

Here, a novel method, called the DBM filter, was proposed for random noise attenuation in seismic data. This method is an adaptive filter that applies the median operation to noisy pixels and leaves healthy pixels unchanged. The results of DBM filtering on different types of seismic data (synthetic data, a shot gather, and a seismic section) proved that it is an effective method for removing random noise. The S/N of different types of seismic data was improved significantly by using this filter. After suppressing random noise from the seismic section, the lateral continuity of seismic events was improved, and hence the interpretability of data was enhanced.

Also, it should be noted that DBM filtering is able to attenuate random noise, while the frequency range of information is not affected considerably. In other words, by using the DBM filter, we are able to attenuate random noise without affecting the seismic information that can be useful in seismic interpretation. Indeed, the DBM filter could strike a balance between eliminating random noise and protecting useful information. These advantages of the DBM filter confirm its robustness for seismic random noise attenuation.

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