RANDOM NOISE REDUCTION USING A HYBRID METHOD BASED ON ENSEMBLE EMPIRICAL MODE DECOMPOSITION

WEI CHEN[1], DONG ZHANG[2] and YANGKANG CHEN[3]*

[1] *Institute of Geophysics and Petroleum Resources, Yangtze University, Daxue Road 111, Caidian District, Wuhan 430100, P.R. China. cwjycd@163.com*
[2] *State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum, Fuxue Road 18, Beijing 102200, P.R. China. zhangdongconan@sina.com*
[3] *Bureau of Economic Geology, John A. and Katherine G. Jackson School of Geosciences, The University of Texas at Austin, University Station, Box X, Austin, TX 78713-8924, U.S.A. chenyk1990@gmail.com*
** Present address: Oak Ridge National Laboratory, One Bethel Valley Rd., Oak Ridge, TN 37831, U.S.A.*

(Received May 25, 2016; revised version accepted March 25, 2017)

ABSTRACT

Chen, W., Zhang, D. and Chen, Y., 2017. Random noise reduction using a hybrid method based on ensemble empirical mode decomposition. *Journal of Seismic Exploration*, 26: 227-249.

We have proposed a novel hybrid random noise reduction method based on ensemble empirical mode decomposition (EEMD) and wavelet threshold filtering. Firstly, the frequency band ranges of effective signal and noise in the initial seismic data set are studied by Fourier spectrum analysis method. Secondly, we make use of EEMD method to obtain the intrinsic mode functions (IMFs) of each original noisy trace. Wavelet threshold filtering is then applied to the high frequency IMFs of each trace to acquire the new denoised high frequency IMFs. Finally, by stacking the filtered high frequency IMFs with the low frequency IMFs and the trend item, we can obtain the ultimately denoised seismic data set. The proposed approach is confirmed via two synthetic data examples and one field data example. The results demonstrate that the proposed approach can achieve much cleaner denoising performance without harming most useful signals.

KEY WORDS: ensemble empirical mode decomposition (EEMD), wavelet threshold filtering, seismic data, random noise reduction.

INTRODUCTION

Reducing random noise is extremely important in almost every aspect of seismic exploration including data processing, inversion and interpretation (Huang et al., 2016; Li et al., 2016; Chen et al., 2016). Because of the challenges and economic saving in currently popular simultaneous-source acquisition techniques, advanced random noise attenuation for prestack seismic

0963-0651/17/$5.00

data is becoming even more demanded (Beasley et al., 1998; Berkhout, 2008; Xue et al., 2016; Gan et al., 2016c).

During the last several decades, various random noise reduction methods have been proposed. The simplest random noise attenuation approach is the mean filter based approach, e.g., stacking (Liu et al., 2009; Yang et al., 2015b). Meanwhile, Median filter method is often used to attenuate spike-like random noise (Liu, 2013; Gan et al., 2016b). The most classic method is f-x deconvolution proposed by Canales (1984), which is capable of enhancing the vertical resolution through denoising while losing the effective signal obviously. A forward and backward prediction filter is used in Wang (1999) for obtaining better denoising performance. Singular value decomposition (SVD) proposed by Ulrych et al. (1988) can preserve effective signal at most, but the signal-to-noise ratio of denoised data is lower. Gan et al. (2015) applied SVD along the geological structure in order to utilize the spatial pattern structure of seismic data and reduce the damages of useful signal caused by SVD. Also, a variety of time-frequency transform methods (Liu et al., 2016c,b) are introduced to ramdom noise attenuation. Methods such as spectral decomposition presented by Yang et al. (2015a), local signal and noise orthogonalization introduced by Chen and Fomel (2015), and compressive sensing based on curvelet transform (Liu et al., 2016a; Zu et al., 2016) can separate the noise and signal effectively, but all of them have negative effect when facing the complex seismic data.

Wavelet transform is a traditional high resolution time-frequency method, and is often used to reduce random noise in seismic data by selecting accurate threshold. Physical wavelet frame denoising method proposed by Zhang and Ulrych (2003) applied a new wavelet frame for noise suppression based on the characteristics of seismic data, which is effective even for seismic signals contaminated by strong coherent noise, such as ground roll or air waves. Mao and Gao (2006) proposed a denoising method for prestack seismic data based on wavelet transform and Monte Carlo simulation. However, wavelet transform method strongly depends on soft or hard threshold, and the denoising result is not desired when facing rapid trace-by-trace variation. Recently, some novel methods have been proposed to suppress the random noise, such as Bayesian inversion (Yuan et al., 2012) or Bayesian inversion with directional difference constraints (Yuan and Wang, 2013). These two methods can extract noise from seismic data effectively based on inversion theory, however, they are time-consuming. Another interesting and effective method is waveform shaping method (Chen and Jin, 2016), which separates the noise and useful signal by shaping the estimated wavelet and the inverted model to a more admissible model. Nevertheless, the waveform shaping method cannot preserve the weak signal.

Furthermore, most methods mentioned above need to subdivide the data into small local windows where the events are linear, however, we cannot well analyse local characteristics of non-linear and non-stationary signals. Huang et al. (1998) proposed empirical mode decomposition (EMD) to solve non-linear and non-stationary problems in geophysics and other fields. EMD can nearly decompose a signal which contains various frequency components into corresponding frequency signals adaptively. Thus, EMD can resolve the non-linear and non-stationary problems effectively. The dominant frequency of the intrinsic mode function (IMF) decomposed by EMD monotonically decreases, and we can remove the high-frequency components to obtain the denoised data considering the dominant frequency of random noise is higher than useful signals (Chen et al., 2014; Chen, 2016; Gan et al., 2016a).

EMD (Huang et al., 1998; Chen et al., 2014; Gan et al., 2016a) and f-x EMD (Chen and Ma, 2014) are used to remove random noise adaptively, and the residual data hardly contains useful signal. Although EMD can solve most seismic data denoising problems with non-linear and non-stationary signals, Wu and Huang (2009) found EMD cannot overcome mode mixing due to signal interruption. Because of lack of robustness, the mode mixing problem is one of the biggest drawback for EMD. Specifically, mode mixing has been defined as any IMF consisting of oscillation frequencies of dramatically disparate scales. When mode mixing problem exists, different frequency components are mixed in one or more IMFs, which causes difficulties in interpreting the time frequency distribution. For this reason, Wu and Huang (2009) superposed signals with white noise to avoid mode mixing, which is the so-called ensemble empirical mode decomposition (EEMD). Considering seismic data are always non-linear and non-stationary, EEMD is widely applied to the field of noise reduction. But the conventional EEMD cannot reduce the noise contained in the high frequency IMFs effectively. Especially when suppressing the noise in multichannel seismic data, selecting the same high-frequency components for all the traces inevitably results in the loss of useful signals.

In this paper, we introduce wavelet threshold filtering to first reduce noise in the high frequency IMFs in order to separate noise more accurately during the subsequent EEMD. Comparing to f-x deconvolution method, wavelet noise reduction method and EEMD method, the proposed method shows better performance. The rest of the paper is organized as follows: firstly, we present brief reviews of principles of the EMD and EEMD algorithms, and then we point out the intrinsic disadvantage and put forward our proposed algorithm. In this part, we also review wavelet transform which is of highly importance in our proposed denoising method, and we discuss the advantage of combination of wavelet threshold filtering and EEMD compared to only using EEMD or wavelet threshold filtering. Secondly, we compare both the synthetic and field experiments using EEMD method, wavelet noise reduction method, f-x deconvolution method and our proposed method, respectively. Finally, we conclude our proposed approach and give some perspectives and insights about our method.

METHOD

The denoising method proposed in this paper combines EEMD method and wavelet thresh old filtering. The theoretical basis of EEMD is EMD, and its aim is to adaptively decompose a non-linear and non-stationary signal into a set of band-limited signals, which are called intrinsic mode functions (IMFs) and are considered to be stationary. The IMFs have two characteristics: (1) the number of extrema and the number of zero crossings must either be equal or differ at most by one; (2) at any point, the mean value of the envelopes defined by the local maxima and the local minima is nearly close to zero (Huang et al., 1998). The two characteristics are necessary to ensure that each IMF has a narrow frequency band by preventing frequency spreading due to asymmetric waveforms (Han and Mirko, 2013). EMD is able to separate the signal according to the data characteristics. The IMFs computed recursively represent the initial components from the signal. The separation method uses the envelopes defined by the local maxima and the local minimums of the signal. Cubic splines are utilized to interpolate all the local maxima and minimums respectively, and then the average of the upper and lower envelopes is obtained. When subtracting the average, the quasi-IMF appears. If this quasi-IMF is the IMF we desire, we can import the Cauchy criterion (Huang et al., 1998). If the quasi-IMF is not the IMF, the circulation continues. The sifting process terminates when the average of the upper and lower envelopes is nearly zero everywhere. EMD can analyse complicated signals effectively, however, mode mixing problem exists. Wu and Huang (2009) proposed the EEMD to eliminate the mode mixing effect, which is a auxiliary noise analysis method based on EMD via adding a certain extent Gaussian noise to the initial signals. Here, we give the general workflows of EEMD according to Wu and Huang (2009).

1. Superposition of initial signal s(t) with w(t) yields S(t):

$$S(t) = s(t) + w(t) \quad . \tag{1}$$

2. Decompose S(t) by EMD method:

$$S(t) = \sum_{i=1}^{n} c_i + r_n \quad , \tag{2}$$

where c_i (i = 1,⋯,n) is the i-th intrinsic mode function; r_n is the trend item; the above algorithm of EMD is according to Wang (2001).

3. Add different white noise $w_j(t)$ to signal s(t) and repeat the steps (1) and (2):

$$S_j(t) = s(t) + w_j(t) \quad , \tag{3}$$

$$S_j(t) = \sum_{i=1}^{n} c_{ij} + r_{jn} \quad . \tag{4}$$

4. Take corresponding average IMFs as the final IMFs:

$$c_i = (1/N) \sum_{i=1}^{N} c_{ij} \quad . \tag{5}$$

5. Take corresponding average r_n as the final trend item:

$$r_n = (1/N) \sum_{i=1}^{N} c_{ij} \quad . \tag{6}$$

EEMD is actually a noise-assist method, which is capable of eliminating the mode mixing and displaying a better separation performance compared to EMD. The principle of EEMD is as follows: when added white noise which is uniformly distributed throughout the time-frequency space, the time-frequency space splits into different components by the filter group. When the background white noise with uniform distribution is added to the signal, the IMFs of different scales can be automatically mapped to the appropriate scale associated with the background white noise. Each individual test may produce a very noisy result because each additive noise component includes both the signal and the additional white noise. Since noise is different in each individual test, the noise can be eliminated when using enough sampling points in EEMD. The average of all the test results is considered to be the last result, and the mean result of the persistent part is the initial signal itself. In general, the frequency of IMFs in eq. (6) almost decreases by negative powers of 2. Thus, the noise intensity of each IMF is becoming weaker so that the low frequency IMF is almost the low frequency component of the desired denoised signal. The high frequency IMFs are time-varying but stationary noisy signals, which are suitable to be reduced by wavelet threshold filtering. Using the relationship between modulus maximum and local singularity of seismic signal, noise reduction by wavelet threshold filtering detects the modulus maximum position and amplitude of wavelet transform coefficients. Due to negative singularity, the amplitude of noise decreases as the scale increases. So if the amplitude of local modulus maximum increases quickly as the scale decreases, it means the singularity is mainly controlled by noise, which however should be removed. In this paper, we adopt the algorithm of wavelet threshold filtering as follows:

1. Transform the high frequency IMFs using wavelet transform.

2. Search the modulus maximum points corresponding to wavelet transform coefficient at each scale.

3. Search the largest amplitude of extreme points and set it to A. We choose the following filtering threshold:

$$T_0 = \{[\log_2(1 + 2\sqrt{N})]/(J + Z)\}A \quad . \tag{7}$$

   where N is presupposed noise power; J is the selected largest scale; Z is a constant and usually set to 2.

4. Search the maximum line and remove the points that are off the maximum line.

5. Reconstruct signal corresponding to modulus maximum points, and the signal reconstructed is the denoised IMF components.

The complete workflows of the proposed random noise reduction method in this paper are summarized as follows:

1. Transform the high frequency IMFs using Fourier transform and analyse the frequency band distribution of useful signal and noise.

2. Transform the seismic data by EEMD.

3. According to the frequency range of noise, select the high frequency IMFs for wavelet threshold filtering and preserve the low frequency IMFs and the trend item.

4. Reconstruct the desired denoised seismic data set by adding the new high frequency IMFs, the low frequency IMFs and the trend item together.

The detailed workflows of the proposed noise reduction method are shown in Figs. 1 and 2.

EXAMPLES

In this section, we use two synthetic data examples and one field example to test the denoising performance of the proposed approach, which is EEMD combined with wavelet threshold filtering. In order to test the performance of our proposed method, we firstly make the noise-free synthetic seismic data as

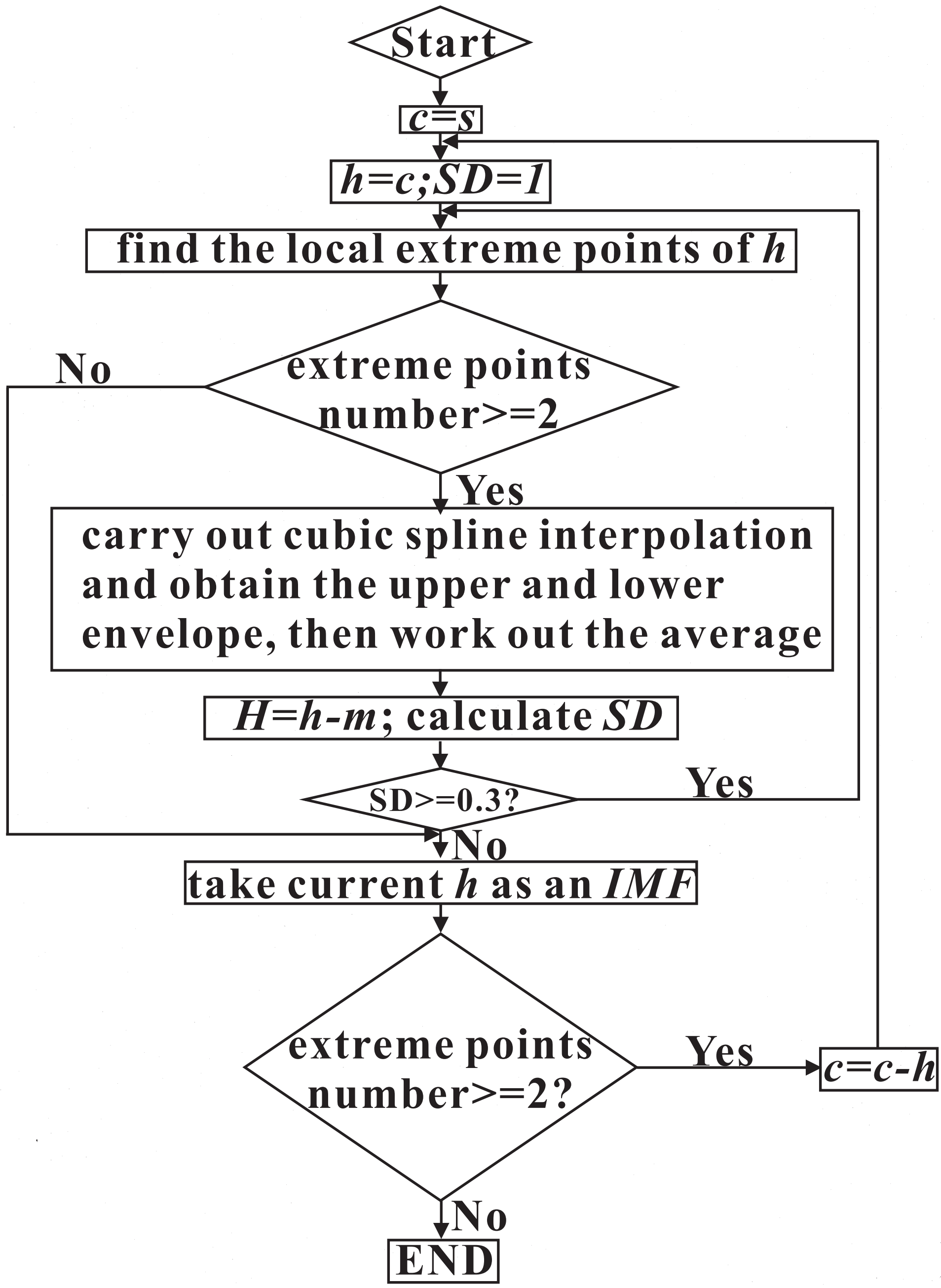


Fig. 1. The workflows of EMD.

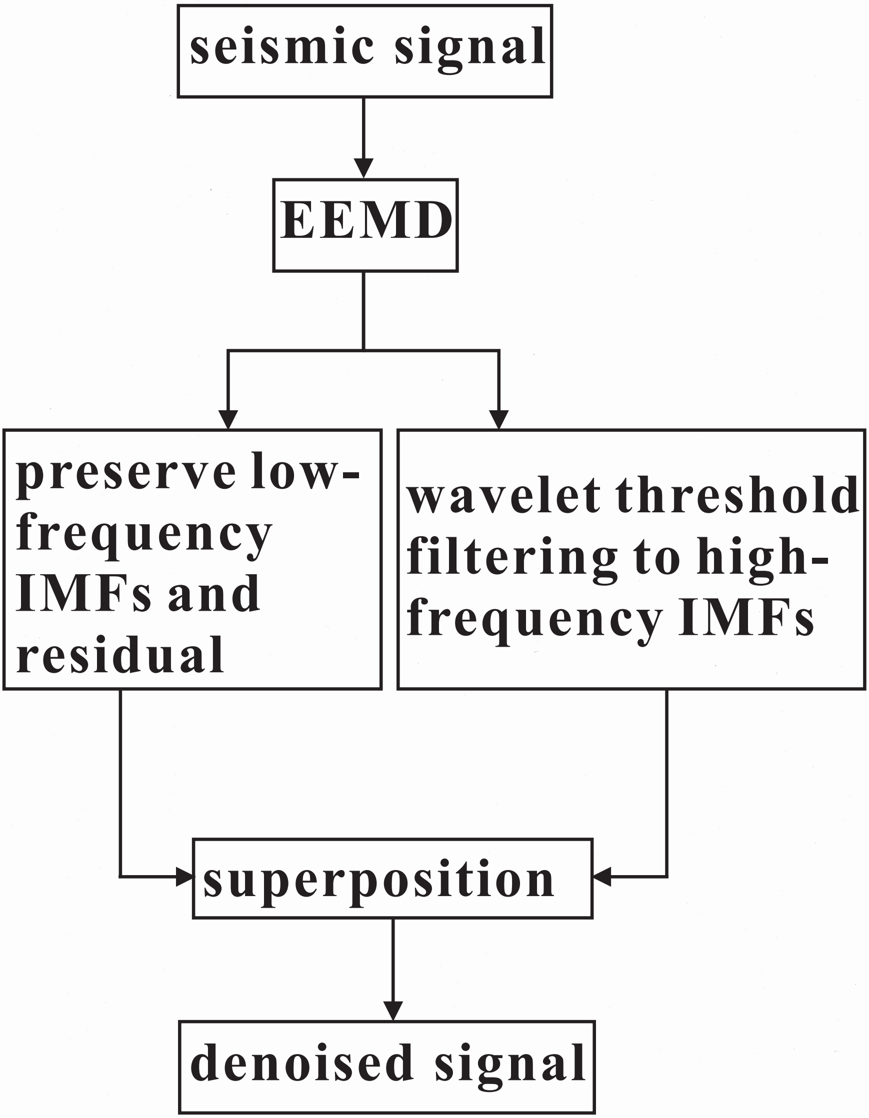


Fig. 2. The detailed workflows of the proposed noise reduction method.

shown in Fig. 3(a), which consist of 21 traces and 501 time samples with a sample interval of 1 ms. This is a very simple model, which only contains a horizontal event and a set of cross events. Specifically, a horizontal event and a sloping axis form the cross events. There is a break point in the cross events, which can be used to test the end effect of the proposed algorithm.

In order to numerically test the denoising performance, we define the criterion for comparison as noise-to-signal ratio (NSR):

$$NSR = 10\log_{10}[\,\| S_{noise} \|_2^2 \,/\, \| S_{signal} \|_2^2\,] \ , \qquad (8)$$

where S_{noise} denotes the noise and S_{signal} denotes the signal.

By adding 50% (NSR = 0.5) Gaussian noise to the noise-free profile, we generate a noisy profile as shown in Fig. 3(b). Obviously, it is easy to identify the break point in the noisy profile, but the resolution of three events is lower than the clean profile. Next, we compare the proposed denoising method with EEMD method, wavelet noise reduction method and f-x deconvolution method. Relative standard deviation of Gaussian noise in EEMD is 0.6 with the total number of 300. The denoised results and removed noise of four methods are shown in Figs. 4 and 5, respectively. Unlike the other noise reduction method, our proposed method adaptively matches its decomposition to the smoothness of the data [Fig. 4(d)]. This offers the opportunity to implement different schemes for different events .

The proposed strategy is the simplest one and has led to good performance on nearly all data sets we have tested.

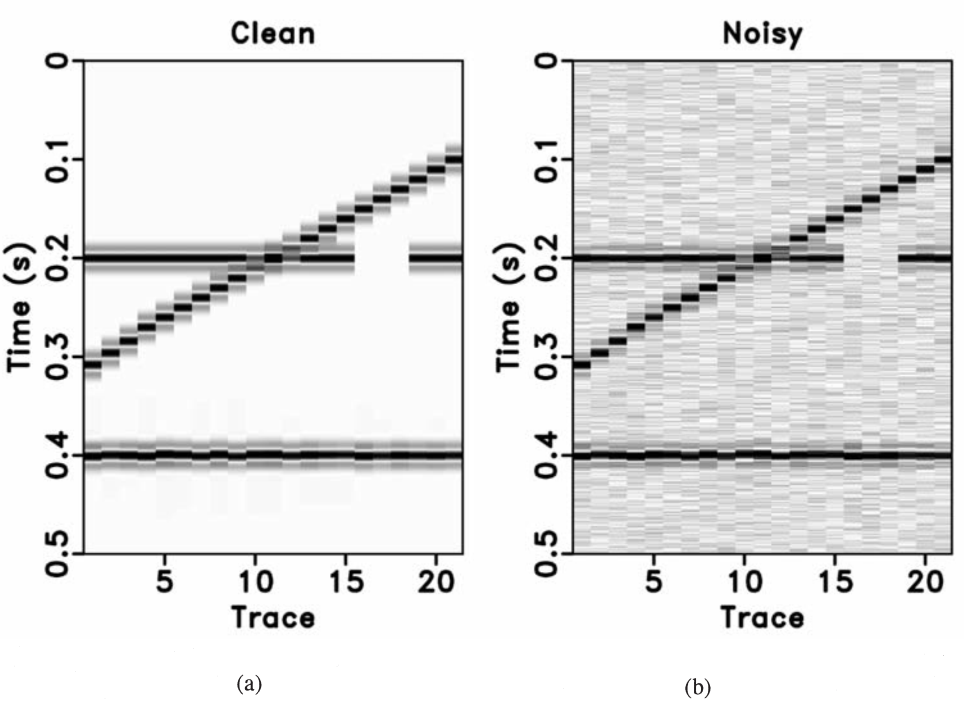


Fig. 3. The first synthetic example. (a) Clean data. (b) Noisy data.

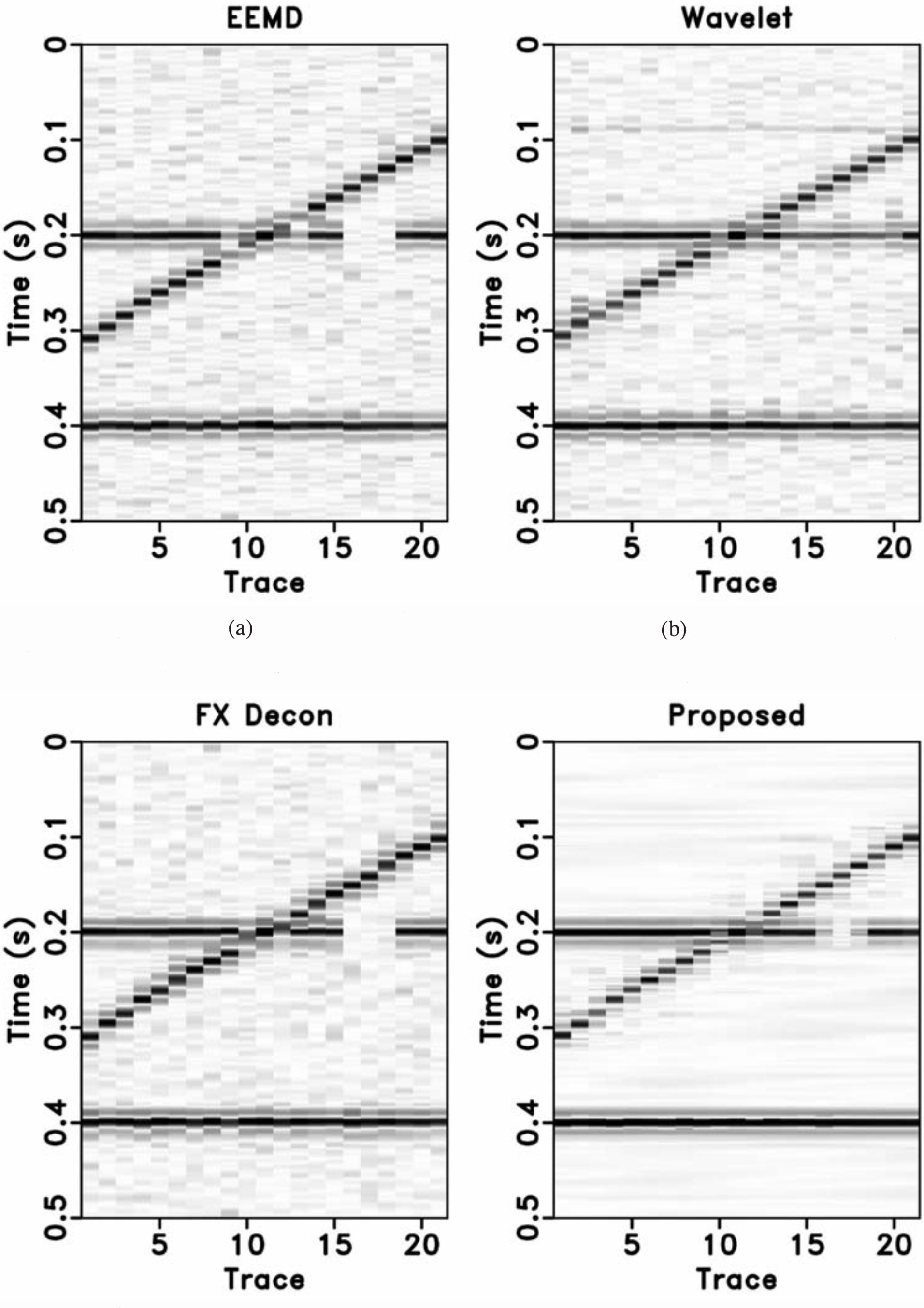


Fig. 4. Denoised results of the first synthetic example using (a) EEMD, (b) wavelet noise reduction, (c) f-x deconvolution, and (d) the proposed method.

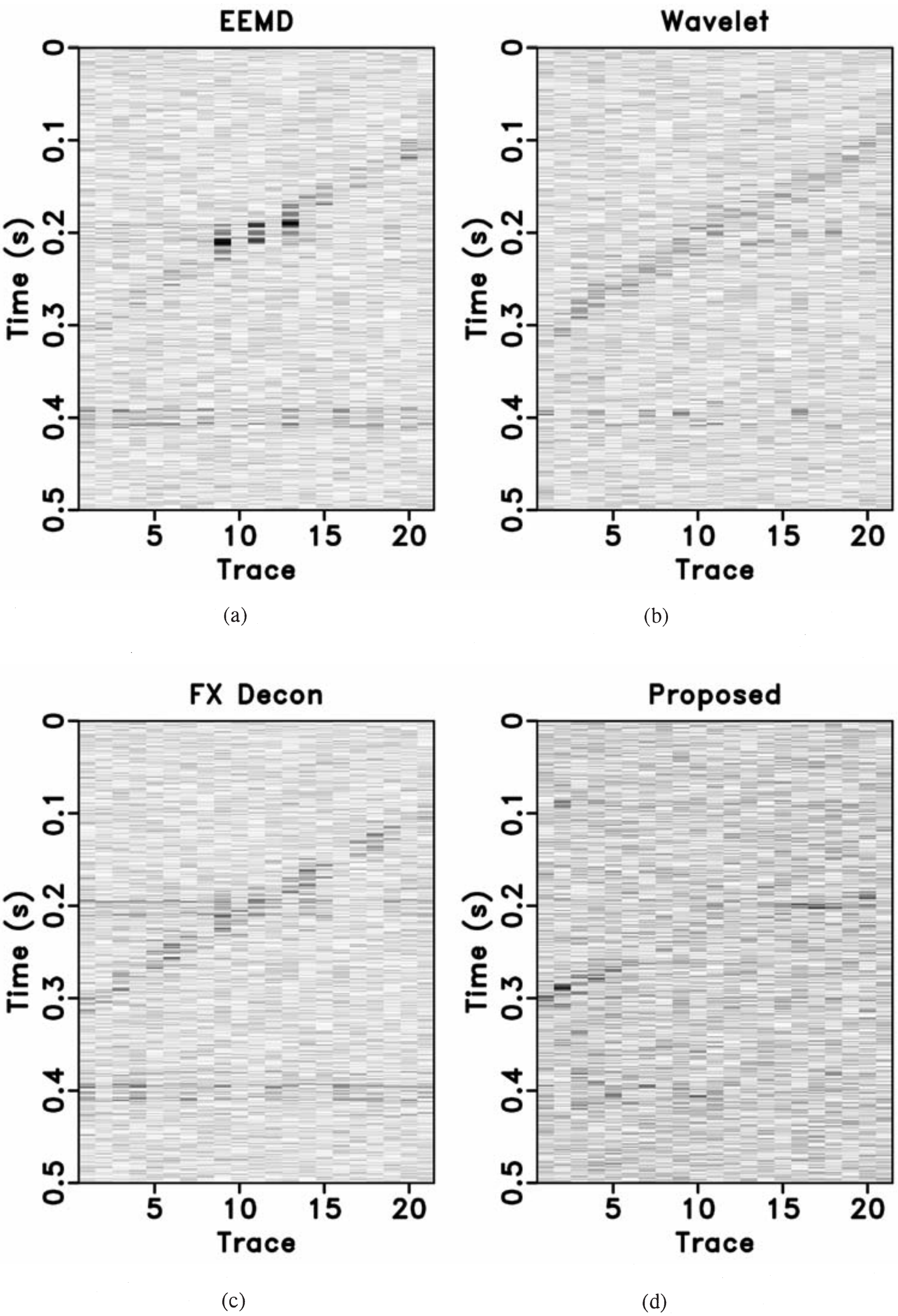
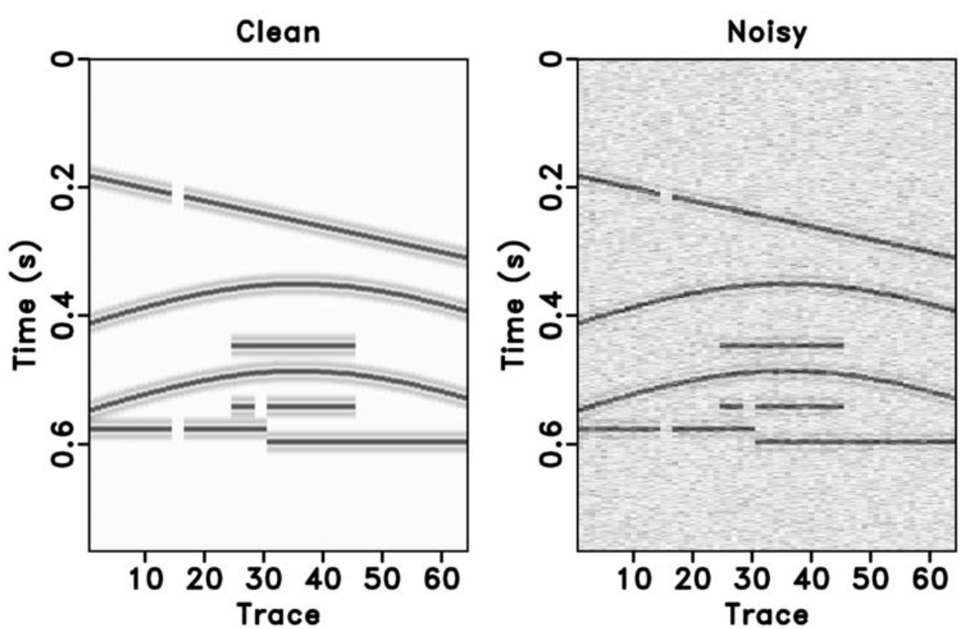


Fig. 5. Removed noise of the first synthetic example using (a) EEMD, (b) wavelet noise reduction, (c) f-x deconvolution, and (d) the proposed method.

From the comparison of four methods, it can be seen that our proposed method is better than the other three methods. Firstly, from the point of removed noise, the proposed method is very random, which is consistent with the added noise [Fig. 5(d)]. Although the removed noise of EEMD method is also very random [Fig. 5(a)], the corresponding denoised section remains some obvious useful signal [Fig. 4(a)]. The denoised section of f-x deconvolution [Fig. 4(c)] is relatively better than wavelet noise reduction method [Fig. 4(b)], especially the removed noise of wavelet noise reduction method [Fig. 5(b)] is random except for the three break points. In other words, the break point in the denoised section by wavelet noise reduction method is hard to identify, thus the lateral resolution is lower than the other three methods. However, the vertical resolution of f-x deconvolution [Fig. 4(c)] and wavelet noise reduction methods [Fig. 4(b)] is lower than our proposed method [Fig. 4(d)]. Secondly, the seismic traces of our proposed method are much closer to the initial noise-free synthetic data in Fig. 3(a). The EEMD is not a recursive spatial filtering method, therefore, no signal energy is passed to the next sample. By changing the parameters of EEMD or wavelet threshold filtering, our proposed method can produce the better results.



(a) (b)

Fig. 6. The second synthetic example. (a) Clean data. (b) Noisy data.

Next, we make a complicated synthetic data set consisting of 64 traces and 765 samples with a sample interval of 1 ms as shown in Fig. 6(a). Except for one dip event and one horizontal event, there are two fault structures with three break points and two anticline structures.

Like the first example, we generate a noisy profile as shown in Fig. 6(b) by adding 50% (NSR = 0.5) Gaussian noise to the noise-free profile. As displayed in the noisy profile, it is hard to identify the three break points especially for the break point on the dip event, meanwhile, the boundary between useful signal and noise is blurring. In order to compare with EEMD method, wavelet noise reduction method and f-x deconvolution method, we display four corresponding denoising results in a fair manner. That is to say, the best results are shown in this paper. Relative standard deviation of Gaussian noise in EEMD is also 0.6 with the total number of 300. The denoised results and - removed noise are shown in Figs. 7 and 8, respectively. From the performances of four noise reduction methods, we can see the removed noise of the proposed method is the most random comparing to the other three methods, which is consistent with the added noise. Although the removed noise of f-x deconvolution method is also very random, the corresponding denoised section obviously remains some random noise. The denoised section of f-x deconvolution is relatively better than the wavelet noise reduction method, especially the removed noise of wavelet noise reduction method is random except for the three break points. However, the vertical resolution of both f-x deconvolution and wavelet noise reduction methods is lower than our proposed method. Moreover, the seismic traces of proposed method are closer to the initial noise-free synthetic data in Fig. 6(a). Obviously, the proposed method enhances the signal-to-noise ratio of any coherent energy and is therefore more appropriate for this test data set, and also our method is better in protecting edges and break points than the other three methods.

From the two synthetic examples, it can be seen that my our proposed method is actually more efficient than the conventional methods.

To further test the denoising performance, our method is applied to a real post-stack seismic data set consisting of 501 traces with a sample interval of 2 ms as shown in Fig. 9. The data set mainly includes discontinuous events, non-stationary events and faults. In other words, we face the challenges of the non-linear and non-stationary signals in this data set. From Fig. 9, it is obvious that the useful signal is blurred by noise. The signal is no longer mapped to a superposition of simple harmonics but rather a superposition of non-linear and non-stationary ones. In order to compare with EEMD method, wavelet noise reduction method and f-x deconvolution method, we display the corresponding denoising results. The denoised results and the removed noise are shown in Figs. 10 and 11, respectively. In this test, relative standard deviation of Gaussian noise in EEMD is 0.8 with the total number of 600. Comparing with

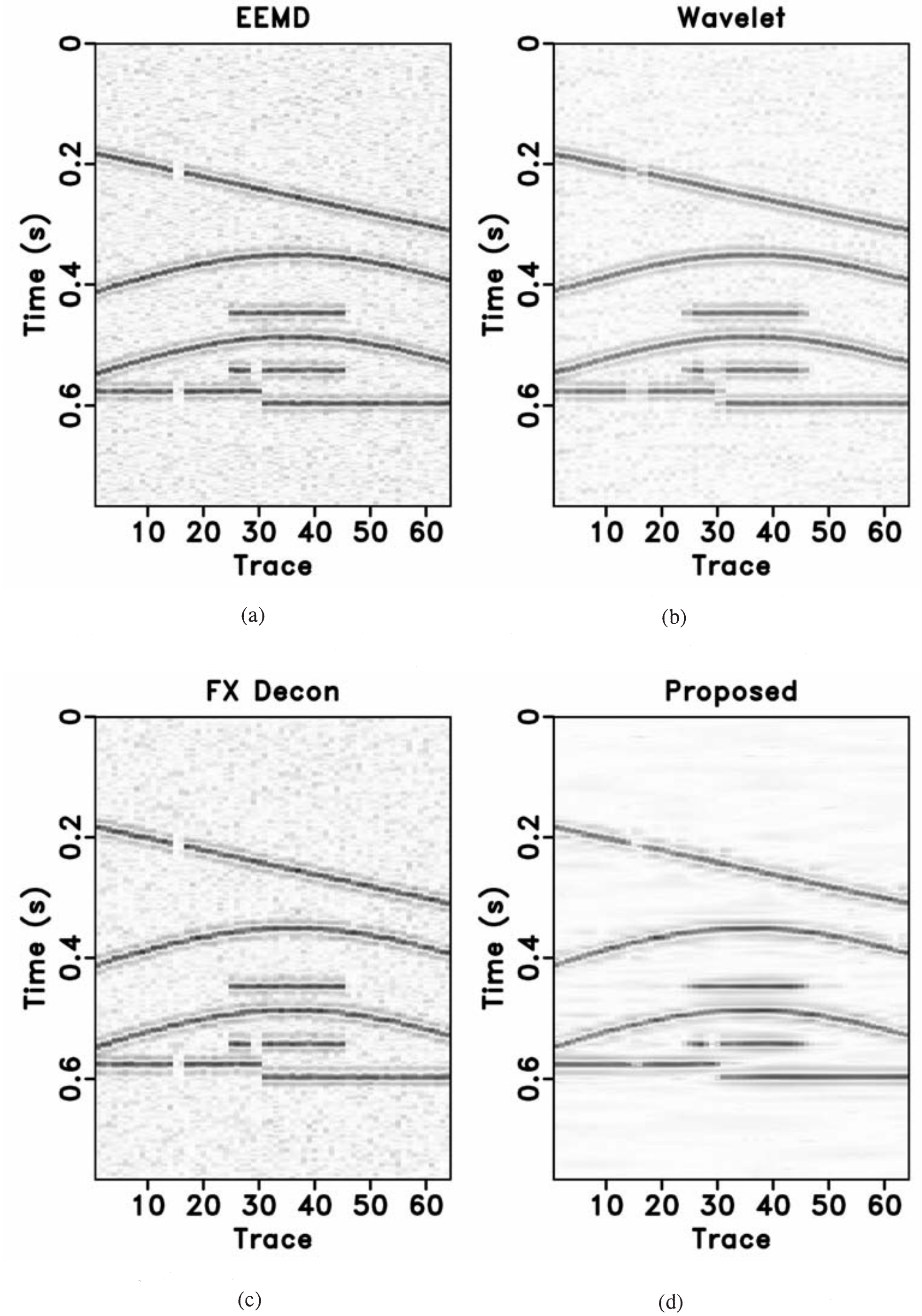


Fig. 7. Denoised results of the second synthetic example using (a) EEMD, (b) wavelet noise reduction, (c) f-x deconvolution, and (d) proposed method.

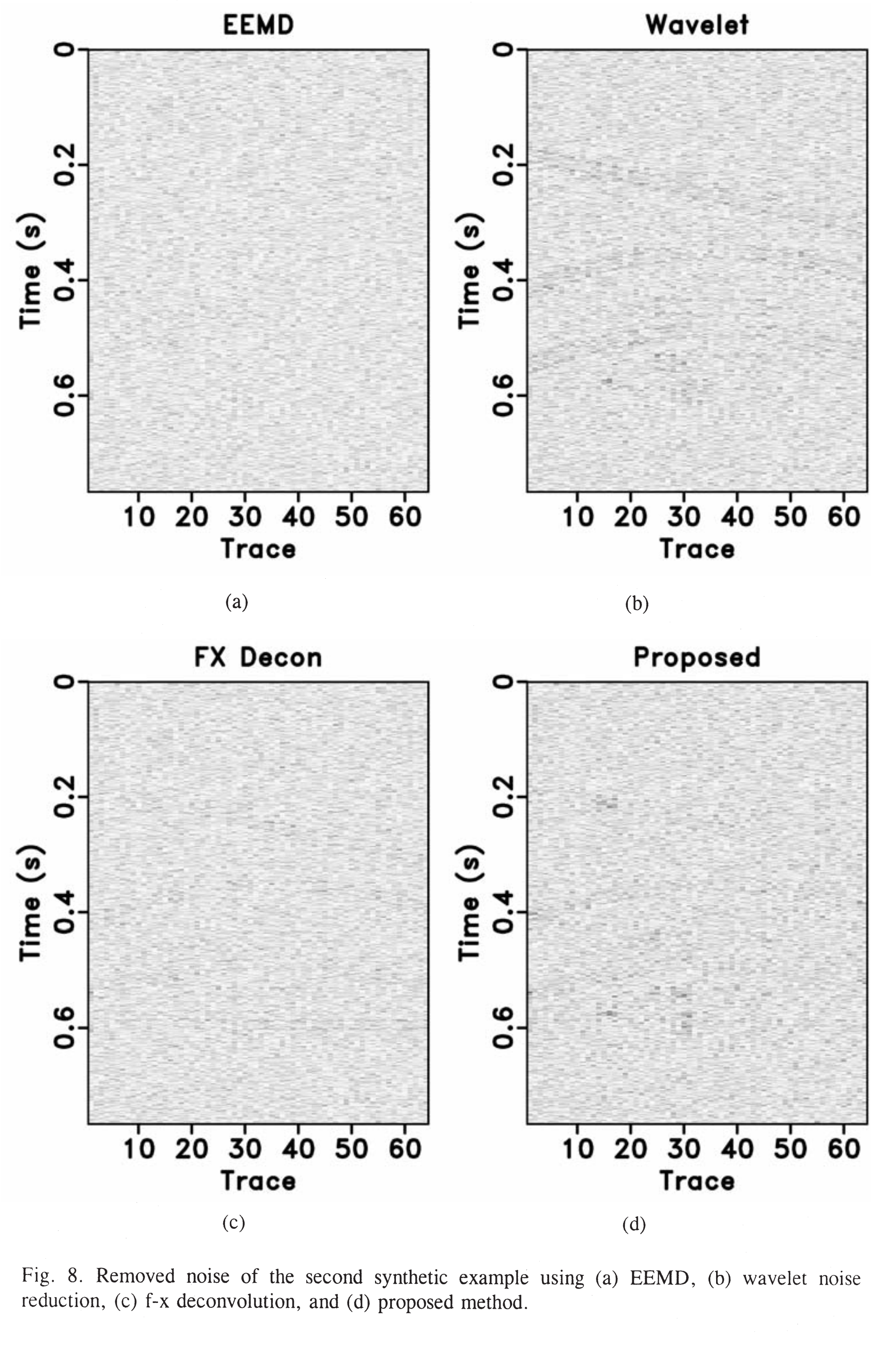


Fig. 8. Removed noise of the second synthetic example using (a) EEMD, (b) wavelet noise reduction, (c) f-x deconvolution, and (d) proposed method.

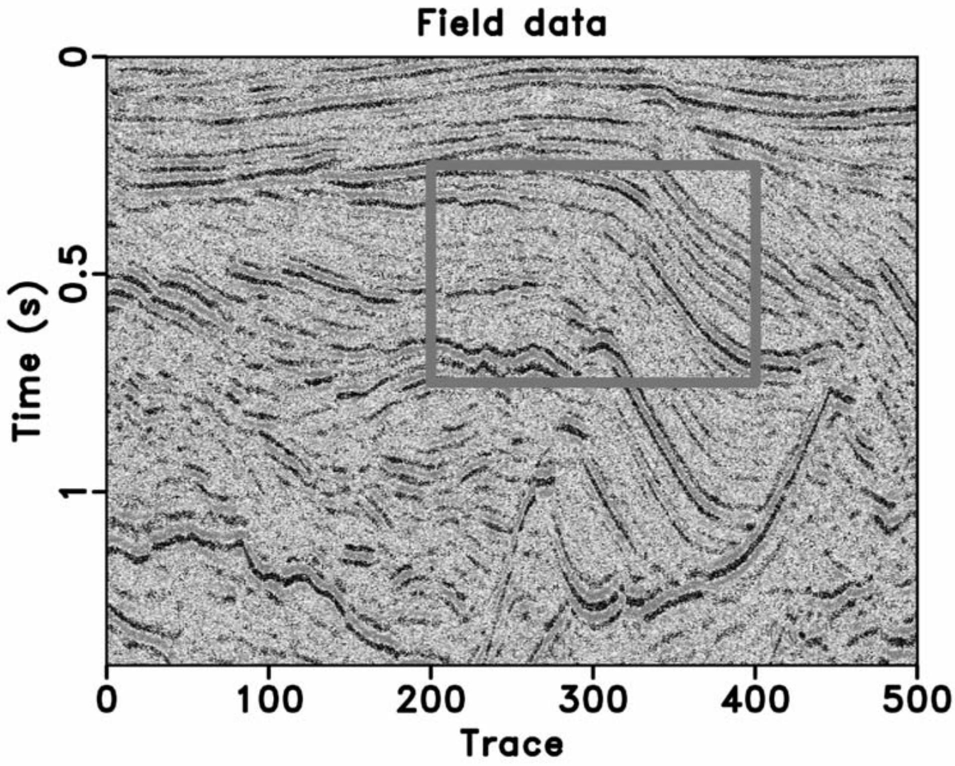
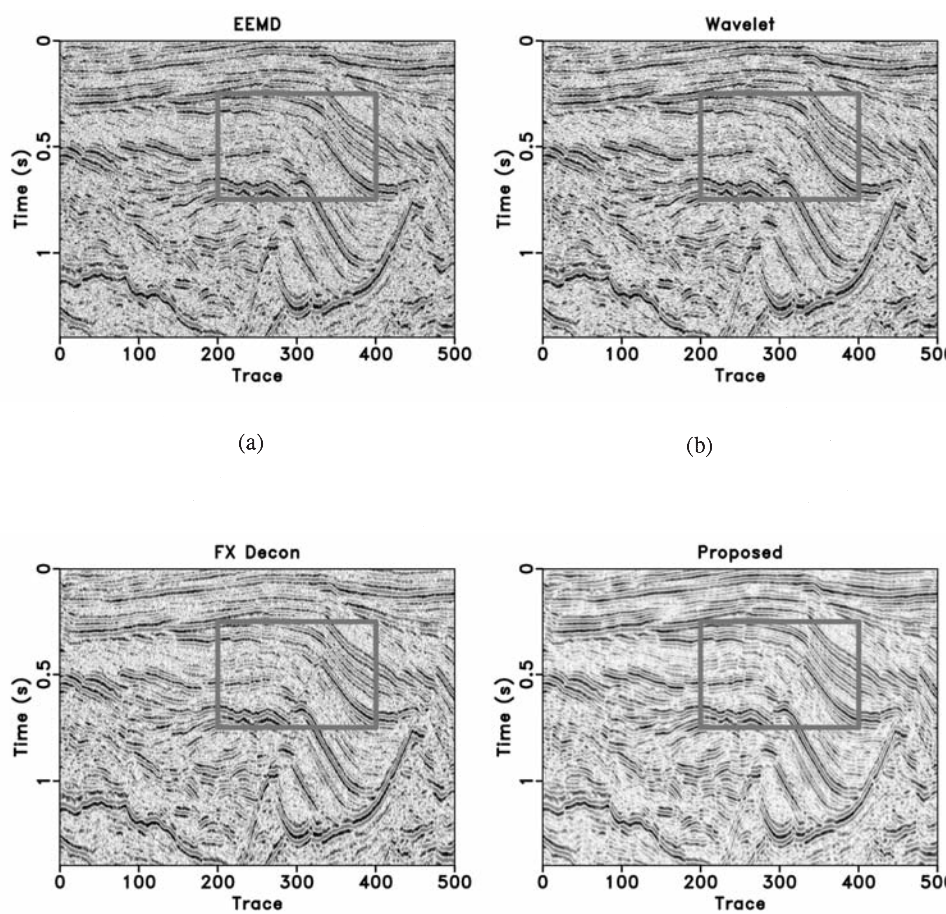


Fig. 9. Field data example.

the noisy and the denoised sections, the latter reflects the strata structure more clearly, especially the obvious fault at 0.75 s in Fig. 10. The overall random noise in Fig. 10 is weaker than the original section.

Our method attenuates some of the background noise but leaves the crossing artifacts untouched (Fig. 11(d)). It also causes amplitude distortion by partially removing useful reflector energy. The denoised section also attenuates some background noise but very little amplitude distortion occurs. More importantly, our method is able to remove the crossing artifacts, which leads to a superior result [Fig. 11(d)]. Especially the removed noise of our method is more random than the other three methods. Besides, the removed noise of the proposed method hardly displays useful structure signal. The removed noise of EEMD method is also very random [Fig. 11(a)], but the corresponding denoised section is not very clean and the resolution is poor [Fig. 10(a)]. The denoised section of f-x deconvolution [Fig. 10(b)] is relatively better than wavelet noise reduction method [Fig. 10(c)], especially the removed noise of wavelet noise reduction method [Fig. 11(c)] is random except for the faults and discontinuous structures. However, the vertical resolution of f-x deconvolution and wavelet noise reduction methods is much lower than our proposed method. It is obvious that our method enhances the signal-to-noise ratio of all the coherent energy. The denoised section of the proposed method is easier to be interpreted. In general, although all four methods accurately retrieve curved events or quasi-linear events, our proposed method has the least signal loss. We then zoom some parts from the noisy field data, the denoised data, and the removed noise for better comparison. The zoomed noisy field data is shown in Fig. 12.



(a) (b)

(c) (d)

Fig. 10. Denoised results of the field data example using (a) EEMD, (b) wavelet noise reduction, (c) f-x deconvolution, and (d) the proposed method.

The zoomed area is highlighted by the red frame box in Fig. 9. The zoomed denoised data is shown in Fig. 13. The corresponding zoomed areas are highlighted in Fig. 10. It is obvious that the denoised results are much cleaner than the noisy field data, and most importantly the denoised data using the proposed approach obtains the cleanest result. The zoomed datasets that correspond to the blue frame boxes shown in Fig. 11 are displayed in Fig. 14. It is salient that the proposed approach can remove the most noise while preserve useful signals very well.

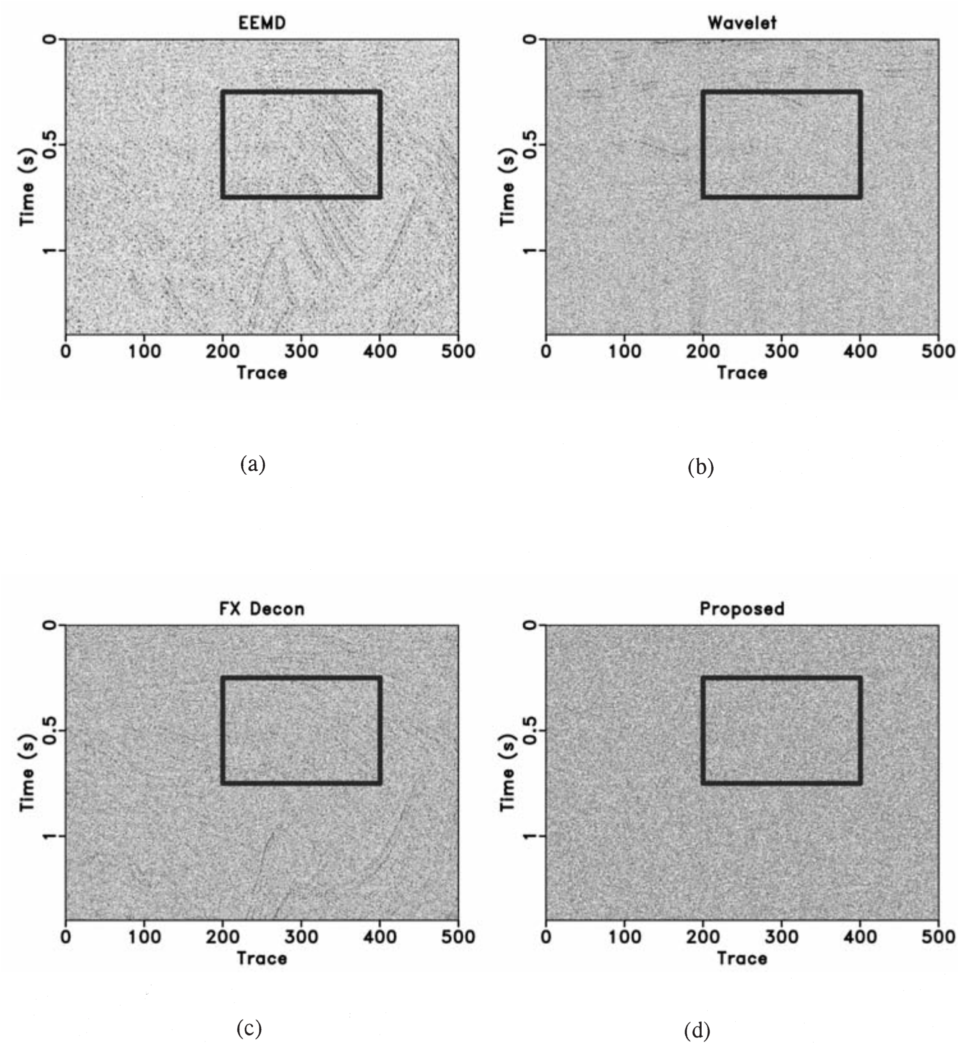


Fig. 11. Removed noise of the field data example using (a) EEMD, (b) wavelet noise reduction, (c) f-x deconvolution, and (d) the proposed method.

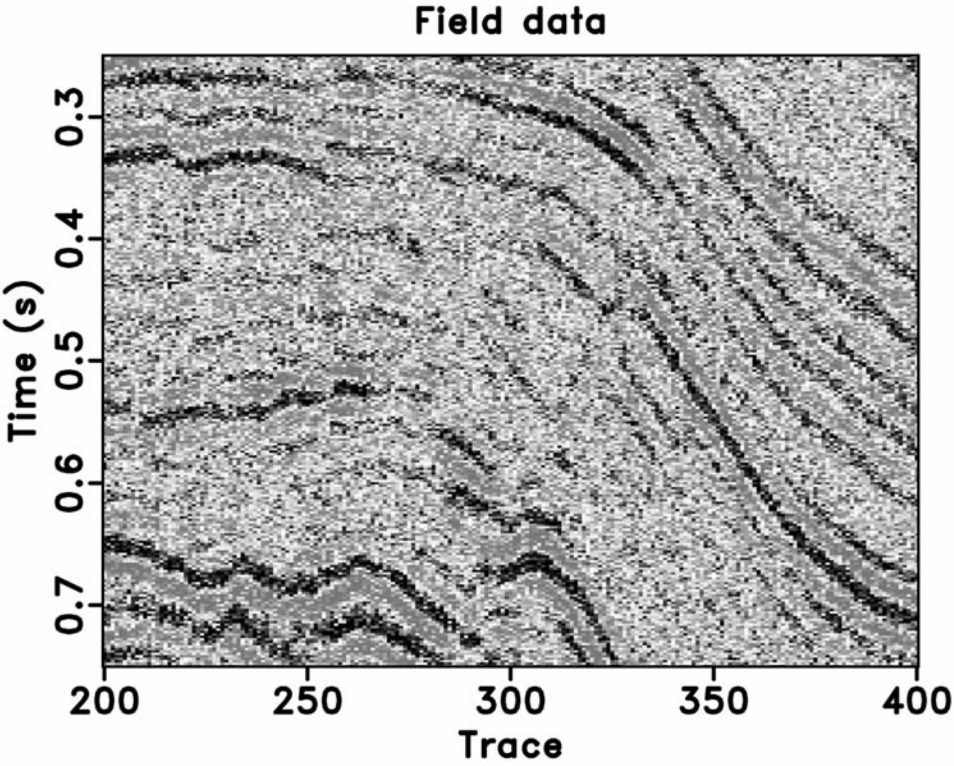


Fig. 12. Zoomed field data example.

Both the synthetic and the real seismic data examples display our method moves more background noise compared to the conventional wavelet noise reduction method. Unfortunately, not all steeply dipping energy is unfavourable and removal of some IMFs could eliminate desired reflections. Thus, when the random noise are very low, our method might remove steeply dipping reflections.

DISCUSSION AND CONCLUSIONS

We have developed a new random noise reduction approach based on wavelet threshold filtering and EEMD which is suitable for non-linear and non-stationary signals. The key idea is to build more pure IMFs than EEMD method to denoise the signal. Wavelet threshold filtering is applied to the high frequency IMFs of each trace to obtain new high frequency IMFs so that our method can reduce the noise in the high frequency IMFs effectively. Application of the proposed method to both synthetic and real seismic data shows good results. Comparing to EEMD method, wavelet noise reduction method and f-x deconvolution method, our proposed method shows better denoising performances.

However,the proposed method is implemented trace by trace, thus, the lateral continuity of denoised section is not optimal. The key factor is that the

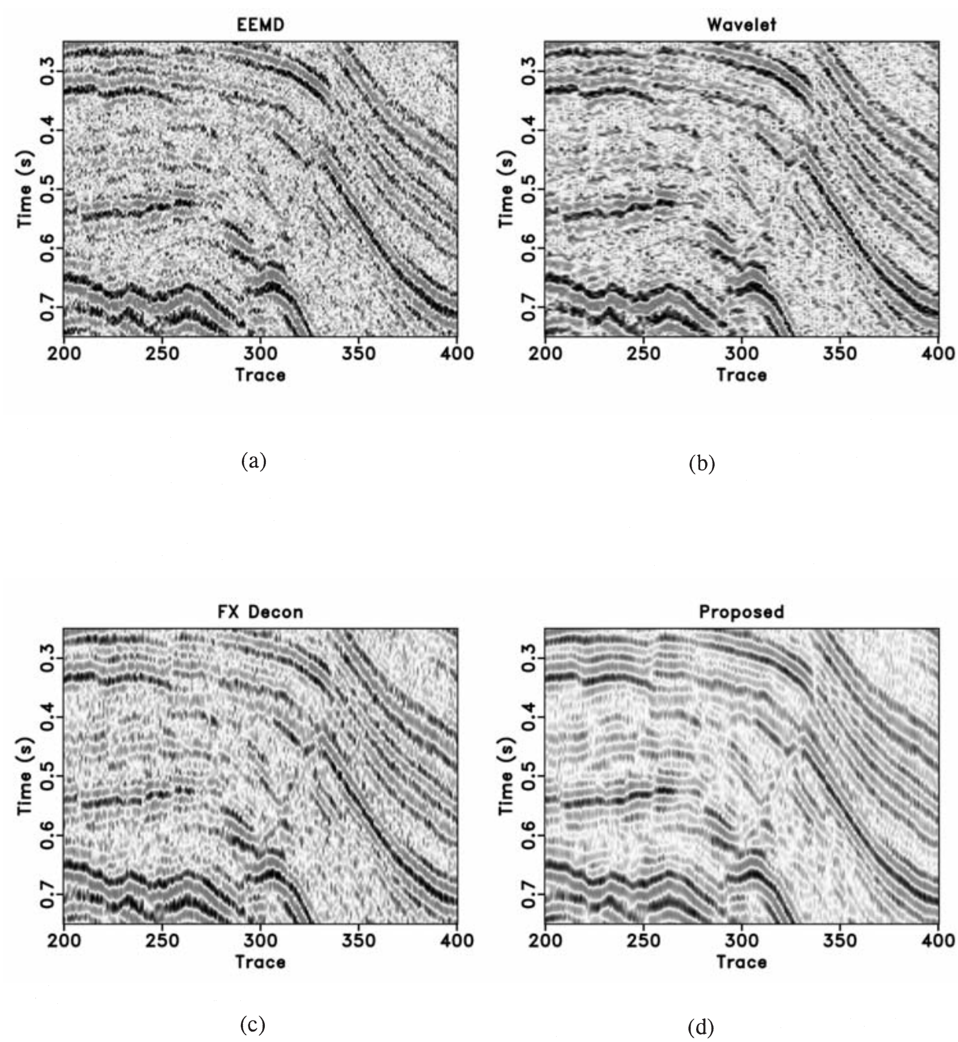


Fig. 13. Zoomed sections of denoised results using (a) EEMD, (b) wavelet noise reduction, (c) f-x deconvolution, and (d) the proposed method.

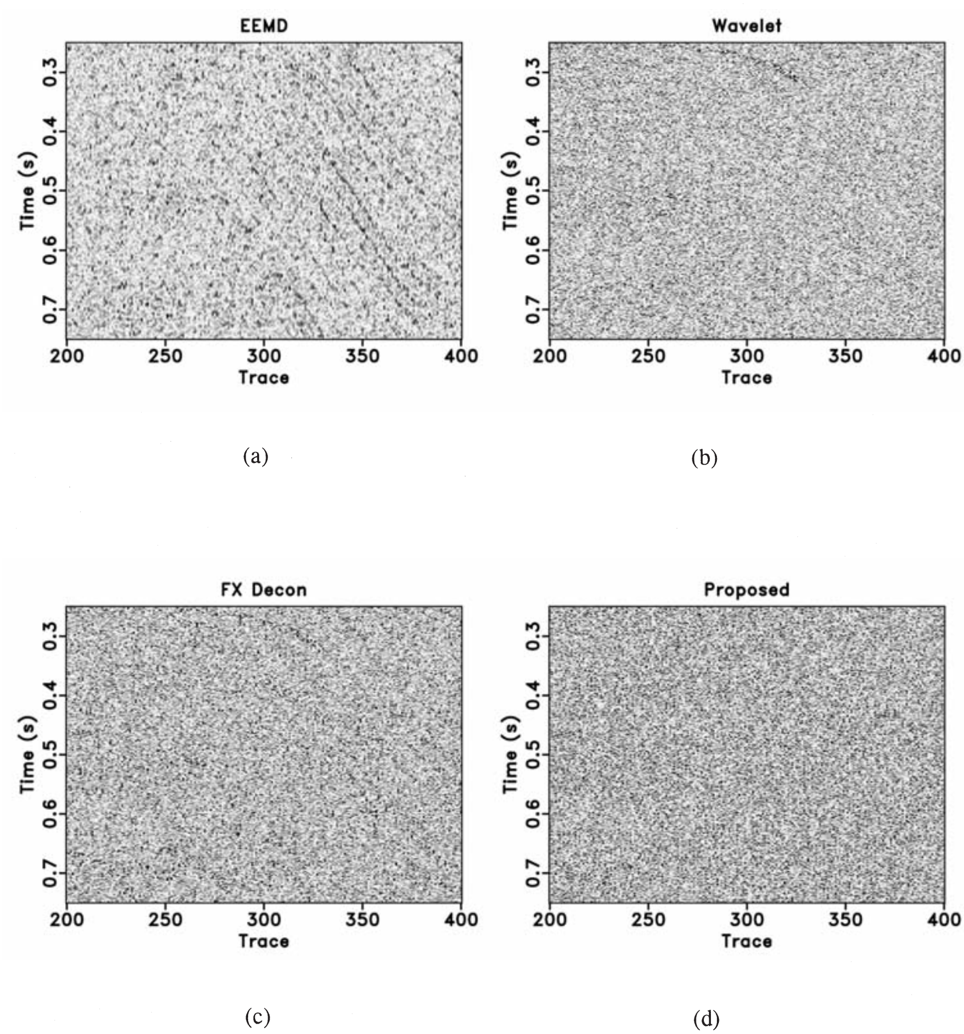


Fig. 14. Zoomed new sections of removed noise using (a) EEMD, (b) wavelet noise reduction, (c) f-x deconvolution, and (d) the proposed method.

number of empirical modes for each trace is different trace by trace, but the high frequency IMFs we selected in our method are fixed. When the structure in the data is complicated, the fixed high frequency IMFs will cause lateral discontinuity. In the future, we plan to investigate how to select the high frequency IMFs according to the trace characteristic, which can improve the adaptivity of the proposed method in this paper.

ACKNOWLEDGEMENTS

The authors would like to thank Qinwen Dong for helpful comments and suggestions on the topic of EEMD. This research is supported by Sinopec Key Laboratory of Geophysics (Grant No. 33550006-15-FW2099-0017).

REFERENCES

Beasley, C.J., Chambers, R.E. and Jiang, Z., 1998. A new look at simultaneous sources. Expanded Abstr., 68th Ann. Internat. SEG Mtg., New Orleans: 133-135.

Berkhout, A.J., 2008. Changing the mindset in seismic data acquisition. The Leading Edge, 27: 924-938.

Canales, L., 1984. Random noise reduction. Expanded Abstr., 54th Ann. Internat. SEG Mtg., Atlanta: 525-527.

Chen, Y., Zhou, C., Yuan, J. and Jin, Z., 2014. Application of empirical mode decomposition to random noise attenuation of seismic data. J. Seismic Explor., 23: 481-495.

Chen, Y., 2016. Dip-separated structural filtering using seislet thresholding and adaptive empirical mode decomposition based dip filter. Geophys. J. Internat., 206: 457-469.

Chen, Y., Ma, J. and Fomel, S., 2016. Double-sparsity dictionary for seismic noise attenuation. Geophysics, 81(2): V17-V30.

Chen, Y. and Fomel, S., 2015. Random noise attenuation using local signal-and-noise orthogonalization. Geophysics, 80(6): WD1-WD9.

Chen, Y. and Jin, Z., 2016. Simultaneously removing noise and increasing resolution of seismic data using waveform shaping. IEEE Geosci. Remote Sens. Lett., 13: 102-104.

Chen, Y. and Ma, J., 2014. Random noise attenuation by f-x empirical-mode decomposition predictive filtering. Geophysics, 79(3): V81-V91.

Gan, S., Chen, Y., Zu, S., Qu, S. and Zhong, W., 2015. Structure-oriented singular value decomposition for random noise attenuation of seismic data. J. Geophys. Engineer., 12: 262-272.

Gan, S., Wang, S., Chen, Y., Chen, J., Zhong, W. and Zhang, C., 2016a. Improved random noise attenuation using fx empirical mode decomposition and local similarity. Appl. Geophys., 13: 127-134.

Gan, S., Wang, S., Chen, Y., Chen, X. and Xiang, K., 2016b. Separation of simultaneous sources using a structural-oriented median filter in the flattened dimension. Comput. Geosci., 86: 46-54.

Gan, S., Wang, S., Chen, Y., Qu, S. and Zu, S., 2016c. Velocity analysis of simultaneous- source data using high-resolution semblancecoping with the strong noise. Geophys. J. Internat., 204: 768-779.

Han, J. and Mirko, V., 2013. Empirical mode decomposition for seismic time-frequency analysis. Geophysics, 78(2): O9-O19.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.-C., Tang, C.C. and Liu, H.H., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc. Roy. Soc. London. Series A: Mathemat., Phys., Engineer. Sci., 454: 903-995.

Huang, W., Wang, R., Chen, Y., Li, H. and Gan, S., 2016. Damped multichannel singular spectrum analysis for 3D random noise attenuation. Geophysics, 81(4): V261-V270.

Li, H., Wang, R., Cao, S., Chen, Y. and Huang, W., 2016. A method for low-frequency noise suppression based on mathematical morphology in microseismic monitoring. Geophysics, 81(3): V159-V167.

Liu, G., Fomel, S., Jin, L. and Chen, X., 2009. Stacking seismic data using local correlation. Geophysics, 74: V43-V48.

Liu, W., Cao, S., Chen, Y. and Zu, S., 2016a. An effective approach to attenuate random noise based on compressive sensing and curvelet transform. J. Geophys. Engineer., 13: 135-145.

Liu, W., Cao, S. and Chen, Y., 2016b. Application of variational mode decomposition in random noise attenuation and time-frequency analysis of seismic data. Extended Abstr., 78th EAGE Conf., Vienna.

Liu, W., Cao, S. and Chen, Y., 2016c. Applications of variational mode decomposition in seismic time-frequency analysis. Geophysics, 81(5): V365-V378.

Liu, Y., 2013. Noise reduction by vector median filtering. Geophysics, 78: V79-V87.

Mao, J. and Gao, J., 2006. On the denoising method of prestack seismic data in the wavelet domain. Expanded Abstr., 76th Ann. Internat. SEG Mtg., New Orleans: 25(1).

Ulrych, T., Freire, J. and Siston, P., 1988. Eigenimage processing of seismic sections. Expanded Abstr., 58th Ann. Internat. SEG Mtg., Anaheim: 525-527.

Wang, Y., 1999. Random noise attenuation using forward-backward linear prediction. J. Seismic Explor., 8: 133-142.

Wu, Z. and Huang, N., 2009. Ensemble empirical mode decomposition: A noise-assisted data analysis method. Advan. Adapt. Data Anal., 1: 1-41.

Xue, Z., Chen, Y., Fomel, S. and Sun, J., 2016. Seismic imaging of incomplete data and simultaneous-source data using least-squares reverse time migration with shaping regularization. Geophysics, 81: S11-S20.

Yang, W., Wang, R., Chen, Y., Wu, J., Qu, S., Yuan, J. and Gan, S., 2015a. Application of spectral decomposition using regularized non-stationary autoregression to random noise attenuation. J. Geophys. Engineer., 12: 175-187.

Yang, W., Wang, R., Wu, J., Chen, Y., Gan, S. and Zhong, W., 2015b. An efficient and effective common reflection surface stacking approach using local similarity and plane- wave flattening. J. Appl. Geophys., 117: 67-72.

Yuan, S. and Wang, S., 2013. Edge-preserving noise reduction based on bayesian inversion with directional difference constraints. J. Geophys. Engineer., 10(2): 123-136.

Yuan, S., Wang, S. and Li, G., 2012. Random noise reduction using bayesian inversion. J. Geophys. Engineer., 9: 60-68.

Zhang, R. and Ulrych, T., 2003. Physical wavelet frame denoising. Geophysics, 68: 225- 231.

Zu, S., Zhou, H., Chen, Y., Qu, S., Zou, X., Chen H. and Liu, R., 2016. A periodically varying code for improving deblending of simultaneous sources in marine acquisition. Geophysics, 81(3): V213-V225.