STACKING SEISMIC DATA BASED ON PRINCIPAL COMPONENT ANALYSIS

JUAN WU and MIN BAI

School of Resources and Environment, North China University of Water Resources and Electric Power, Zhengzhou 450045, P.R. China. wujuan@ncwu.edu.cn

(Received August 28, 2017; revised version accepted June 20, 2018)

ABSTRACT

Wu, J. and Bai, M., 2018. Stacking seismic data based on principal component analysis. *Journal of Seismic Exploration*, 27: 331-348.

Stacking seismic data plays an indispensable role in many steps of the seismic data processing and imaging workflow. Optimal stacking of seismic data can help mitigate seismic noise and enhance the principal components to a great extent. Traditional equal-weight seismic stacking method cannot obtain optimal performance when the ambient noise is extremely strong. We propose applying a principal component analysis (PCA) algorithm for stacking seismic data without being sensitive to noise level. We use both synthetic and field data examples to demonstrate the performance of the presented method.

KEY WORDS: seismic imaging, stacking, principal component analysis, low rank approximation.

INTRODUCTION

Stacking is one crucial step in the seismic data processing and imaging workflow (Tian et al., 2014; Lindstrom et al., 2016; Xie et al., 2017; Bai and Wu, 2017; Huang et al., 2017a; Wang et al., 2018). By summing traces corresponding different shot-geophone distances we can output a much enhanced trace for one specific common midpoint. In seismic imaging,

0963-0651/18/$5.00

stacking of different single-shot images can help improve subsurface illumination (Liu et al., 2011; Chen et al., 2016b, 2017d). Stacking is inherently an anti-noise method because summation over a number of well aligned traces can boost the effective signals and suppress the Gaussian white random noise. However, when noise becomes extremely strong and number of traces for stacking is small, simple summation cannot perform well in suppressing the random noise. For this reason, a number of stacking methods have been proposed in the literature for more robust performance in the case of low signal-to-noise ratio (SNR) (Schoenberger, 1996; Zhang et al., 2015; Chen, 2016; Chen et al., 2017c; Chen, 2017; Liu et al., 2016c; Chen and Jin, 2015; Zhang et al., 2016b; Siahsar et al., 2017a,b,c; Zu et al., 2016b, 2017b).

Li and Gao (2014) proposed a novel method for stacking seismic data in the time-frequency domain (Lin et al., 2015; Liu et al., 2016a,b, 2017). Deng et al. (2016) took the amplitude-versus-offset (AVO) effect into consideration and proposed a weighted stacking method which can handle the amplitude variation phenomenon of CMP gathers. Liu et al. (2009) proposed a similarity-weighted stacking approach that designs the weights of each trace by calculating the local similarity between each trace and a reference trace, and the method was demonstrated to be superior to the state-of-the-art weighted stacking approaches. Yang et al. (2015) proposed a hybrid stacking strategy considering the coherency along both midpoint and offset directions.

In this paper, we propose using a principal component analysis (PCA) (Farrell and Mersereau, 2005; Du and Fowler, 2007) based stacking method. Considering the complicated situations of field seismic data as mentioned above, we propose to extract the principal components of seismic data to reject the extremely strong noise, non-Gaussian noise, outliers, and to enhance the amplitude of the primary signals. The principal components of the data matrix are extracted via solving an optimization problem with low-rank constraint. A singular value decomposition can be used to solve the optimization problem and then the low-rank approximation of the data matrix, which has a high SNR and is close to the ideal NMO-corrected common midpoint (CMP) gather, can be easily obtained. In this paper, we overcome the low SNR problem for pre-stack seismic data during traditional equal-weight stacking. We leverage the PCA theory to extract the most significant energy (e.g., the reflection energy) hidden in the extremely noisy seismic data. The PCA approximation method can minimize the negative influence of ambient noise, outliers, imperfect NMO operation, etc.

METHOD

Stacking of seismic data

Traditional stacking of seismic data is an arithmetic average of all traces in the input seismic gather. Let $x_i(t)$ denote a seismic trace (or a column) in a data matrix **X**, the stacked trace can be expressed as

$$y(t) = \sum_{i=1}^{N} \frac{x_i(t)}{N} \quad , \tag{1}$$

where t is time. $y(t)$ is the stacked zero-offset trace, and N is the number of traces (or columns in the data matrix).

PCA approximated data matrix

Let us suppose the data matrix **X** is composed of signal component **S** and unknown components **E**,

$$\mathbf{X} = \mathbf{S} + \mathbf{E} \quad . \tag{2}$$

The unknown components may contain random noise, erratic noise (e.g., large-amplitude spikes) and abnormal components (e.g., misaligned trace). The traditional equal-weight stacking method is essentially a way to boost the energy of useful signals by summation of neighbor traces and at the same time to suppress the random noise. The stacking process is equivalent to applying a mean filter to the whole gather with filter length designed as half number of the total columns.

However, the equal-weight stacking method can obtain optimal performance only if the unknown components are purely Gaussian white noise and the number of columns is large. When the number of columns is large, the arithmetic mean of Gaussian white noise tends to be zero following the statistic rule. When the data matrix is a slim matrix (i.e., the number of rows is much larger than the number of columns), the traditional stacking method cannot obtain optimal performance even if only Gaussian white noise exists. In this case, we need to seek a different way to approximate the useful components in the data matrix.

Principal component analysis (PCA) is an effective way for estimating the principal components in a give matrix. Extracting the principal components in a seismic data matrix using PCA aims at solving the following problem:

$$\min\|\mathbf{E}\|_F^2 \ , \quad s.t. \quad rank(\mathbf{S}) = k, \ \mathbf{X} = \mathbf{S} + \mathbf{E} \ , \tag{3}$$

where $\|\cdot\|_F^2$ denotes the Frobenius norm. k denotes the rank constraint applied to the target signal components.

Singular value decomposition (SVD) can be used to solve the optimization problem. The SVD of the data matrix **D** can be expressed as (Wang et al., 2017; Zhou et al., 2017b, 2018):

$$\mathbf{X} = \mathbf{U\Sigma V}^T \ . \tag{4}$$

Here, **U** is composed of the eigenvectors of $\mathbf{XX}^T$. **V** is composed of the eigenvectors of $\mathbf{X}^T\,\mathbf{X}$. $\mathbf{\Sigma}$ is a diagonal matrix composed of the decreasing singular values. Let us denote **U**, $\mathbf{\Sigma}$ and **V** in the following form:

$$\begin{aligned} \mathbf{U} &= [u_1, u_2, \cdots, u_N] \ , \\ \mathbf{\Sigma} &= \mathrm{diag}(\sigma_1, \sigma_2, \cdots, \sigma_N) \ , \\ \mathbf{V} &= [v_1, v_2, \cdots, v_N] \ . \end{aligned} \tag{5}$$

The vectors $\mathbf{u}_i$ and $\mathbf{v}_i$ are also called the propagation vectors and the eigenwavelets, respectively. The singular values σ_i are sorted such that $\sigma_1 > \sigma_2 > \cdots > \sigma_N$. They can be obtained by calculating the positive square roots of the eigenvalues of the data covariance matrix $\mathbf{XX}^T$. Eq. (4) can be expressed as:

$$\mathbf{X} = \textstyle\sum_{\mathbf{i=1}}^{\mathbf{N}} \boldsymbol{\lambda}_\mathbf{i}\, \mathbf{u}_\mathbf{i}\mathbf{v}_\mathbf{i}^T \ , \tag{6}$$

where $\mathbf{u}_\mathbf{i}\mathbf{v}_\mathbf{i}^T$ is the rank-one matrix called the i-th eigenimage of **X**. Thus, from eq. (5), the seismic data matrix can be decomposed into N eigenimages, the energy of which corresponds to the value of each element in matrix $\mathbf{\Sigma}$. We can approximate the principal components and eliminate the unknown fluctuation in the data matrix by selecting the first k eigenimages (Freire and Ulrych, 1988; Huang et al., 2016, 2017d; Chen et al., 2016c,d; Huang et al., 2017b; Chen et al., 2017e):

$$\hat{\mathbf{S}}_{\mathrm{svd}} = \textstyle\sum_{\mathbf{i=1}}^{\mathbf{k}} \sigma_i\, \mathbf{u}_\mathbf{i}\mathbf{v}_\mathbf{i}^T \ . \tag{7}$$

Stacking based on PCA

After the PCA approximation of the data matrix $\hat{\mathbf{S}}$ is calculated, the better stacked trace is obtained by computing the arithmetic mean of the principal components along the spatial direction:

$$\hat{y}(t) = \sum_{i=1}^{N} \frac{\hat{s}_i(t)}{N} \quad , \tag{8}$$

where $\hat{y}(t)$ is the stacked trace using the PCA method and $\hat{s}_i(t)$ denotes the i-th column in the PCA approximated data matrix. The detailed algorithm workflow of the PCA based stacking approach can be summarized as:

1. Calculate the SVD of data matrix **X**:

$$[\mathbf{U}, \mathbf{\Sigma}, \mathbf{V}] = \mathrm{SVD}(\mathbf{X}) \quad . \tag{9}$$

2. Calculate the low-rank approximated singular value matrix by selecting the k-largest diagonal elements and setting others zero:

$$\hat{\mathbf{\Sigma}} = \mathrm{diag}(\sigma_1, \sigma_2, \cdots, \sigma_k, 0, \cdots) \quad . \tag{10}$$

3. Calculate the low-rank approximated data matrix

$$\hat{\mathbf{S}} = \mathbf{U}\hat{\mathbf{\Sigma}}\mathbf{V}^T \ . \tag{11}$$

4. Calculate the arithmetic mean of the PCA approximated data matrix according to eq. (8).

Although there have been a lot of different independent denoising algorithms in the literature that can be used to attenuate some noise energy (Li et al., 2016a; Chen et al., 2016a; Li et al., 2016b; Gan et al., 2016a; Liu et al., 2016e; Huang et al., 2017c,e,f; Chen et al., 2017b,a; Zhou et al., 2017a), the proposed PCA based method can serve as the most straightforward and easy-to-use way to enhance the SNR. Besides, most denoising approaches either damage a lot of useful energy, or fail in attenuating enough amount of noise (Chen and Jin, 2015; Zhang et al., 2016a, 2017). The PCA based stacking method should be applied as a routine step in common seismic data processing workflow because of its superb performance and easy implementation. On the other hand, the PCA based stacking strategy creates a new paradigm for looking at the seismic data in a new perspective. The current PCA based stacking method has a main drawback that the traditional PCA algorithm takes a large computational cost. A faster implementation of the PCA algorithm based on the fact that the pre-stack seismic data is usually of a special structure (e.g., "slim" matrix) is the current research focus. Future research topics also include substituting the current PCA framework with more sophisticated algorithms to make the obtained components statistically as independent as possible, such as independent component analysis that is proven to be stronger than PCA (Hyvarinen et al., 2001), where higher order statistics rather than second-order moments are used to determine basic vectors. Moreover, applications in other geophysical problems like seismic data interpolation (Gan et al., 2016b; Zhong et al., 2016; Zu et al., 2016a), seismic migration (Ren and Tian, 2016), seismic inversion (Li et al., 2016c; Zu et al., 2017a), multiple attenuation (Shen et al., 2016; Wu et al., 2016), are also worth being investigated.

EXAMPLES

In this section, we use two synthetic and one field data examples to demonstrate the performance of the PCA based stacking algorithm. The first synthetic example is shown in Figs. 1-3. The noisy data to be stacked is shown in Fig. 1(a). It is a simple example that contains five flattened seismic traces. The data is so noisy that the useful signals are almost buried in the strong noise. The PCA approximated useful signals (principal components in this problem) are shown in Fig. 1(b), where we can see that a large amount of random noise has been effectively suppressed and the useful reflection signals become much distinct.

The traditional equal-weight stacking algorithm just calculates the spatial average of the noisy data [Fig. 1(a)]. The PCA based stacking algorithm instead stacks the PCA approximated data along the spatial direction. Fig. 2(a) presents the result from equal-weight stacking, which still contains a lot of residual noise. Fig. 2(b) shows the stacked trace using the PCA based method. Since in this synthetic example, we have the ground-truth solution, we can quantitatively compare the stacking performance via the signal-to-noise ratio (SNR) measurement. The SNR measurement is designed as follows:

$$\mathrm{SNR} = 10\log_{10}\frac{\|\mathbf{s}_0\|}{\|\mathbf{s}_0-\hat{\mathbf{s}}\|} \quad , \tag{12}$$

where $\mathbf{s}_0$ denotes the ground-truth solution and the $\hat{\mathbf{s}}$ denotes the stacked result. Using this metric, the SNR of the equal-weight stacking method is 1.158 dB while the SNR of the PCA based method is 2.991 dB. To demonstrate the robust performance of the proposed PCA based method, we plot the output SNR diagram varying with increasing noise level in Fig. 3. The noise level is characterized by the noise variance. From Fig. 3 we can observe that the PCA based method is always superior to the traditional equal-weight method in obtaining much higher output SNR. It is also salient that as the noise level increases more, the superiority of the proposed PCA method becomes more distinct. We conclude from this simple synthetic example that the PCA method obtains a much improved stacking performance.

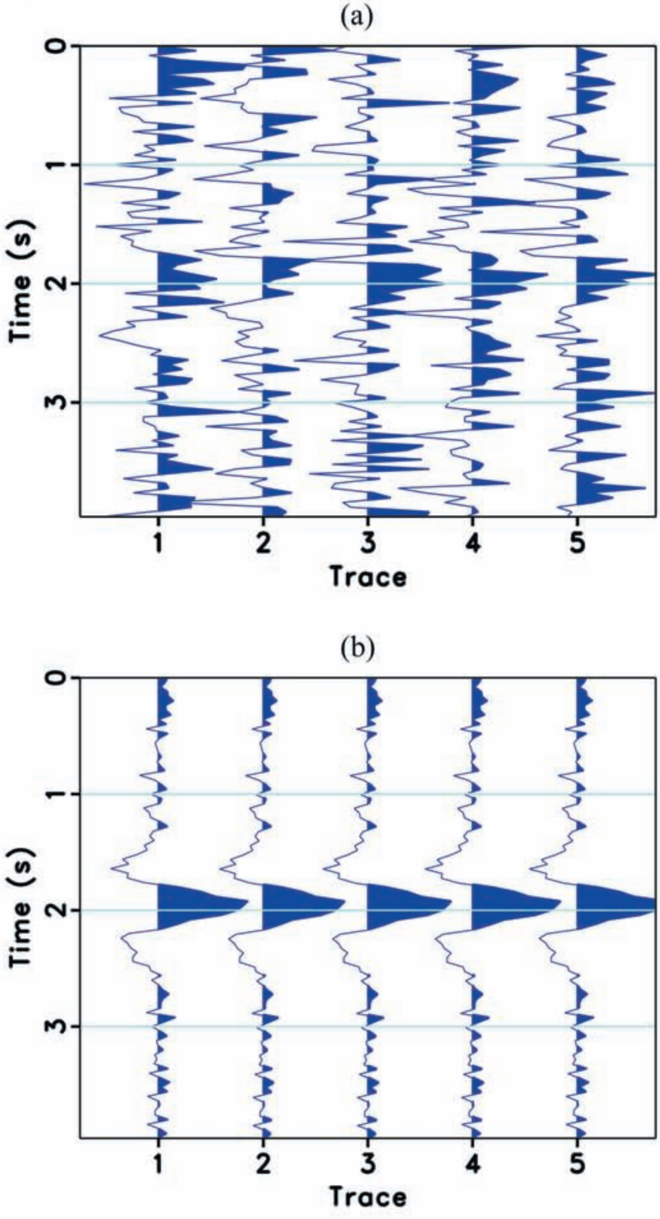
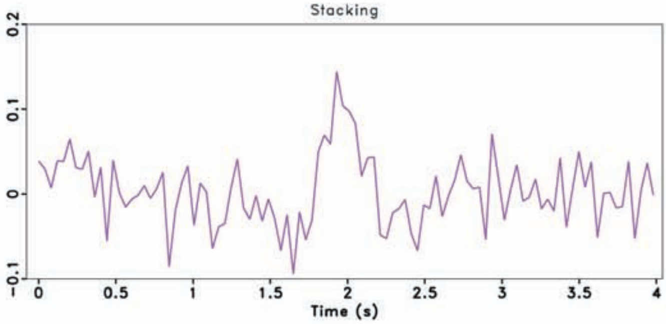


Fig. 1. (a) Flattened synthetic gather. (b) PCA approximated synthetic gather.

(a)



(b)

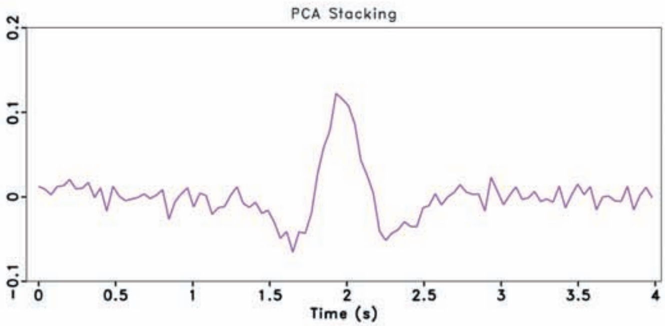


Fig. 2. (a) Stacked trace in the conventional way. (b) Stacked trace using the PCA method.

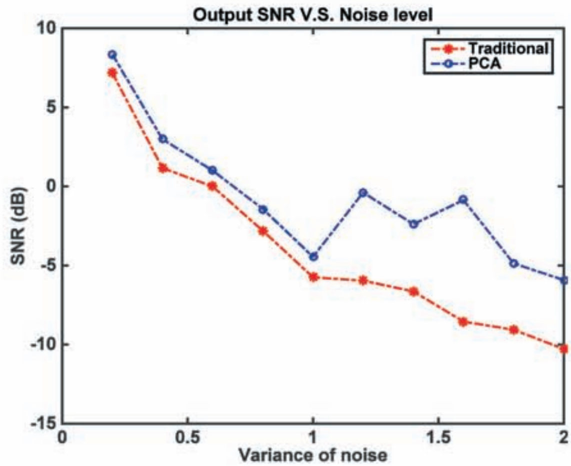


Fig. 3. Output SNRs varying with the input noise levels.

The second example is stacking a prestack 3D seismic data to obtain a stacked image. The prestack seismic data is shown in Fig. 4. The data was also used previously in Gan et al. (2016c). In this example, we add very strong random noise with SNR equal to –3.594 dB. In order to obtain the poststack image, we need first implement normal-moveout (NMO) based velocity analysis on the data and obtain NMO velocity. Then, we use the NMO velocity to atten the gathers, as shown in Fig. 5. We subsequently stack the flattened gathers along the offset direction to output stacked traces for different surface locations. The stacked image roughly depicts the subsurface geological structure. We apply both state-of-the-art equal-weight stacking method and the PCA based method to the flattened gathers and show the stacked images in Figs. 6(a) and 6(b), respectively. From the comparison of stacked images, we can observe that both methods obtain images that show up clear geological structures but the equal-weight method causes strong residual noise while the proposed PCA method obtains an almost noise-free post-stack image. We calculate the SNRs of the two images using the stacked image from clean data as the exact solution. The SNRs of the two methods are 5.171 dB and 11.324 dB, respectively.

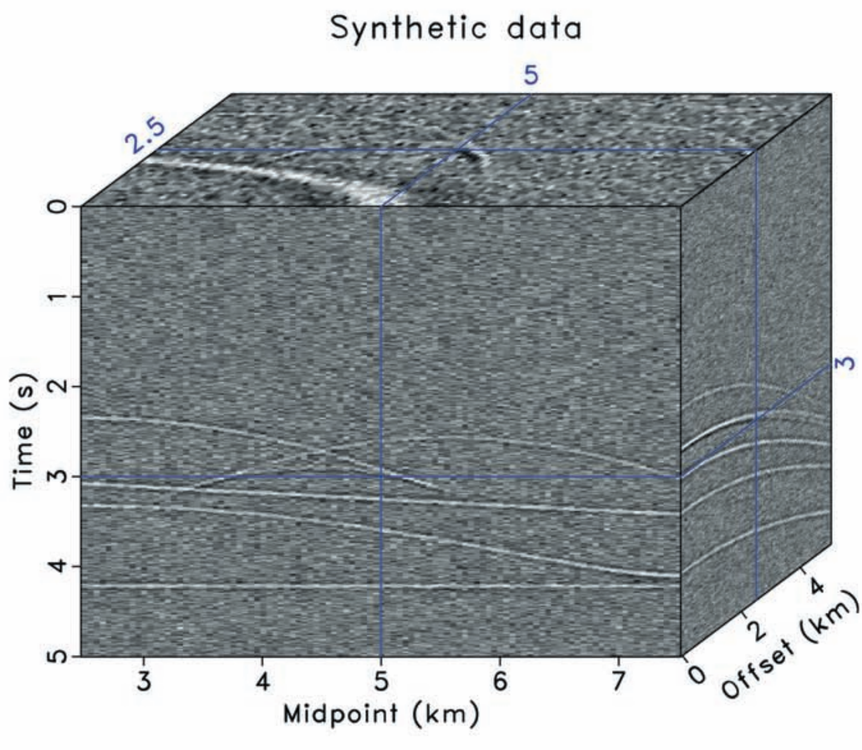


Fig. 4. 3D synthetic seismic data.

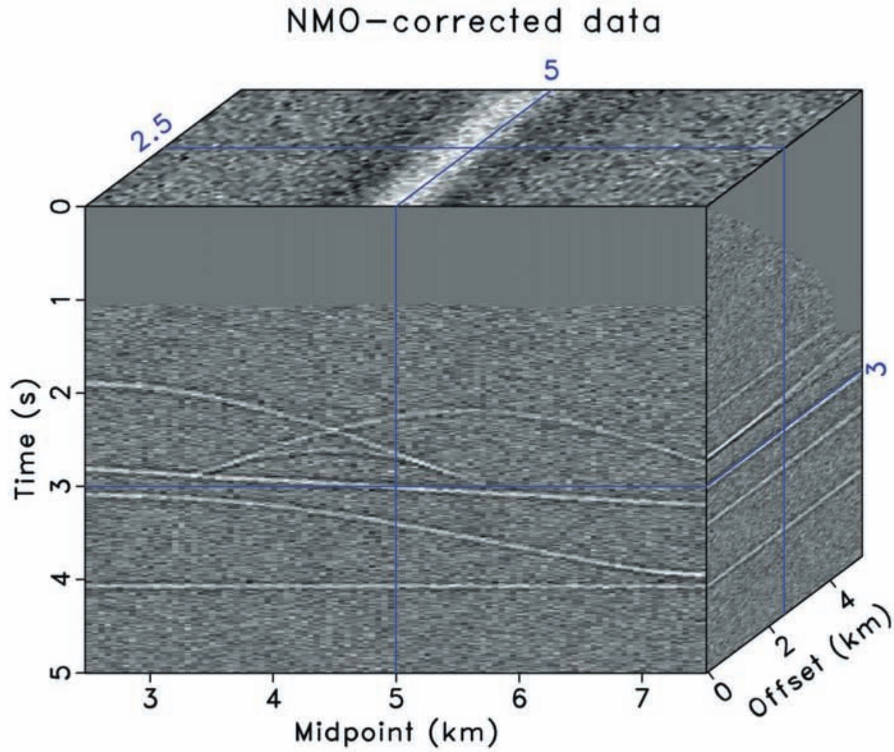
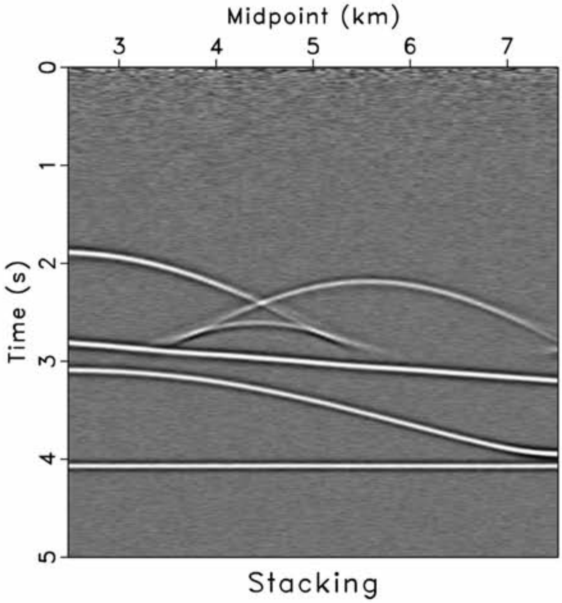


Fig. 5. NMO-corrected seismic data.

We finally demonstrate a field data example. The example is based on a 3D prestack dataset acquired from the Gulf of Mexico (Chen et al., 2015; Chen and Fomel, 2015; Gan et al., 2015; Liu et al., 2016d; Gan et al., 2016d). Fig. 7 shows the raw prestack seismic data. In this data, we have 4000 time samples with 0.001 s sampling rate. There are 250 spatial samples and 24 offset samples. Here we neglect all preprocessing steps and only show the stacked images in Fig. 8 for comparison. For this example, we also show the result from the SNR-based stacking method that was proposed in Neelamani et al. (2006) for more comprehensive comparison. Fig. 8(a) shows the stacked image using the traditional equal-weight method. Fig.8(b) shows the result from the SNR-based stacking method. Fig. 8(c) shows the result from the PCA method. The result show quite clearly that the PCA based methods obtain images with much better spatial coherency and much clearer seismic reflection events. In order to better view the performance, we zoomed a part from each stacked image and show the zoomed sections in Fig. 9, from which we can see a much clearer comparison. The zooming areas are highlighted by the frame boxes in Fig. 8.

(a)



(b)

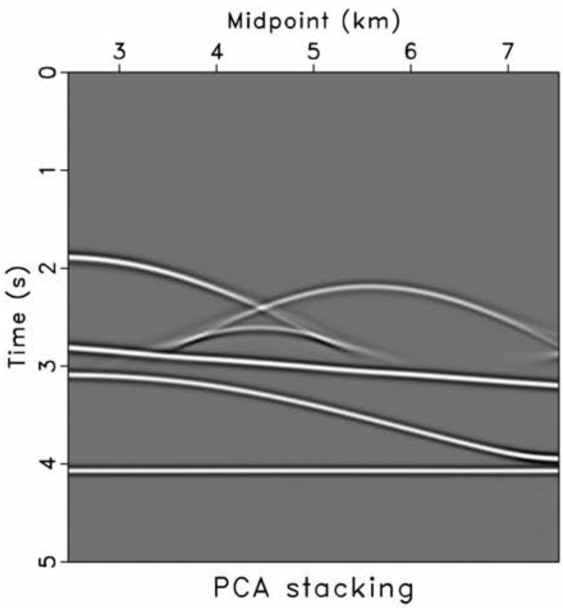


Fig. 6. (a) Stacked result in the conventional way. (b) Stacked result using the PCA method.

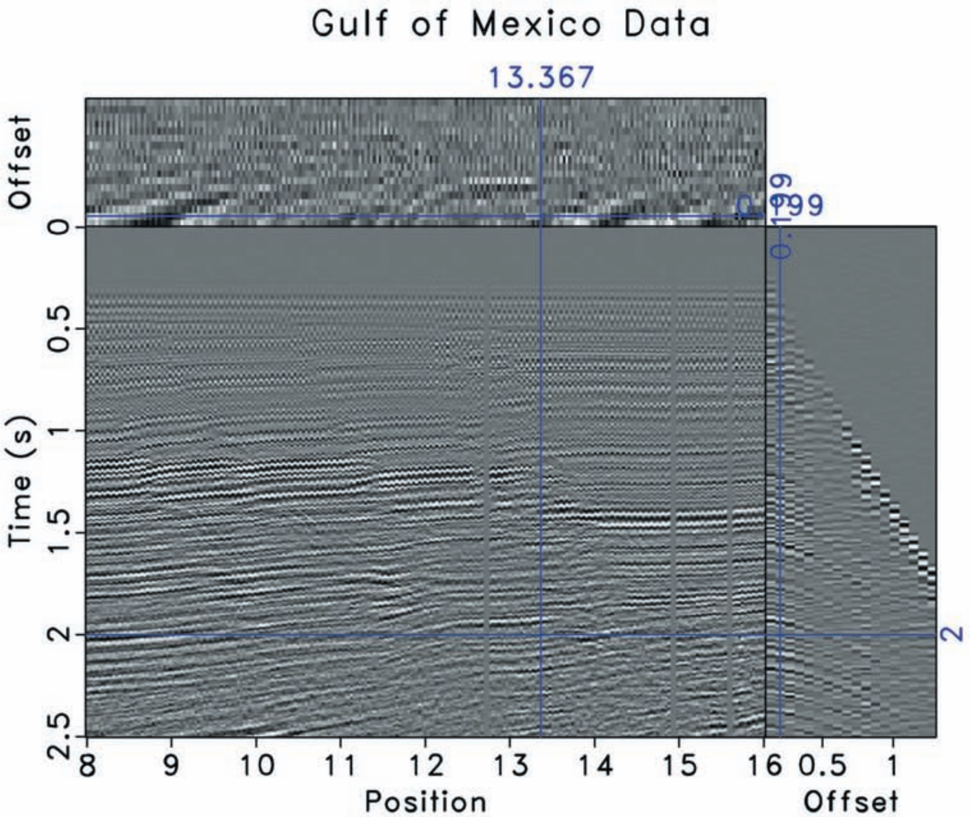


Fig. 7. 3D prestack seismic data.

CONCLUSIONS

Strong random noise will make conventional equal-weight stacking method ineffective in seismic data processing. We have applied an effective principal component analysis (PCA) based method that can be capable of suppressing random noise during the stacking process. The PCA based algorithm tends to extract the principal components, i.e., useful reflection signals, from noisy observations. Numerical results have shown that the PCA based method outperforms the traditional stacking method even more when the noise level becomes extremely high. Both synthetic and field data examples demonstrate the excellent performance of the proposed stacking approach.

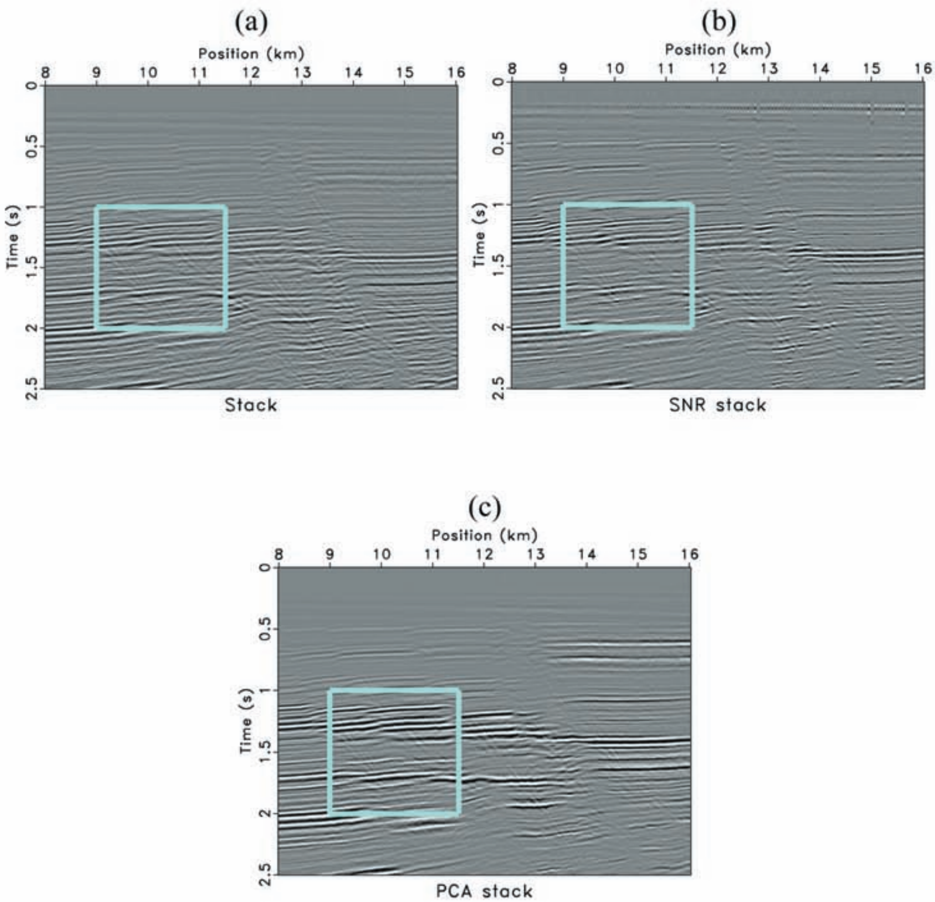


Fig. 8. (a) Traditional stacking. (b) SNR stacking. (c) PCA stacking.

ACKNOWLEDGEMENTS

The project is supported by the National Natural Science Foundation of China (Grant No. 41704121) and the starting fund at North China University of Water Resources and Electric Power (Grant No. 201705002201705003).

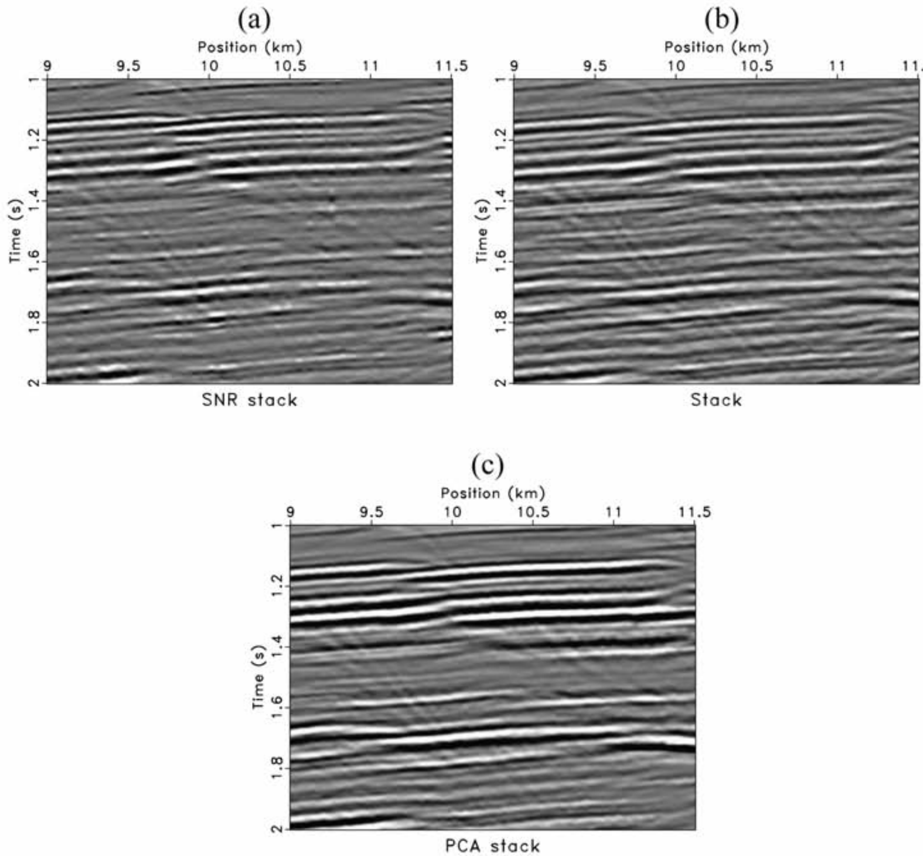


Fig. 9. (a) Traditional stacking. (b) SNR stacking. (c) PCA stacking.

REFERENCES

Bai, M. and Wu, J., 2017. Efficient deblending using median filtering without correct normal moveout - with comparison on migrated images. J. Seismic Explor., 26: 455-479.

Chen, W., Chen, Y. and Liu, W., 2016a. Ground roll attenuation using improved complete ensemble empirical mode decomposition. J. Seismic Explor., 25: 485-495.

Chen, W., Xie, J., Zu, S., Gan, S. and Chen, Y., 2017a. Multiple reflections noise attenuation using adaptive randomized-order empirical mode decomposition. IEEE Geosci. Remote Sens. Lett., 14: 18-22.

Chen, W., Yuan, J., Chen, Y. and Gan, S., 2017b. Preparing the initial model for iterative deblending by median filtering. J. Seismic Explor., 26: 25-47.

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

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., 2017. Fast dictionary learning for noise attenuation of multidimensional seismic data. Geophys. J. Internat., 209: 21-31.

Chen, Y., Chen, H., Xiang, K. and Chen, X., 2016b. Geological structure guided well log interpolation for high-fidelity full waveform inversion. Geophys. J. Internat., 207: 1313-1331.

Chen, Y., Chen, H., Xiang, K. and Chen, X., 2017d. Preserving the discontinuities in least-squares reverse time migration of simultaneous-source data. Geophysics, 82: S185-S196.

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

Chen, Y. and Jin, Z., 2015. Simultaneously removing noise and increasing resolution of seismic data using waveform shaping. IEEE Geosci. Remote Sens. Lett., 13: 102-104.

Chen, Y., Liu, T. and Chen, X., 2015. Velocity analysis using similarity-weighted semblance. Geophysics, 80. A75-A82.

Chen, Y., Zhang, D., Huang, W. and Chen, W., 2016c. An open-source matlab code package for improved rank-reduction 3D seismic data denoising and reconstruction. Comput. Geosci., 95: 59-66.

Chen, Y., Zhang, D., Jin, Z., Chen, X., Zu, S., Huang, W. and Gan, S., 2016d. Simultaneous denoising and reconstruction of 5D seismic data via damped rank-reduction method. Geophys. J. Internat., 206: 1695-1717.

Chen, Y., Zhou, Y., Chen, W., Zu, S., Huang, W. and Zhang, D., 2017e. Empirical low rank decomposition for seismic noise attenuation. IEEE Transact. Geosci. Remote Sens., 55: 4696-4711.

Deng, P., Chen, Y., Zhang, Y. and Zhou, H., 2016. Weighted stacking of seismic AVO data using hybrid AB semblance and local similarity. J. Geophys. Engin., 13: 152-163.

Du, Q. and Fowler, J., 2007. Hyperspectral image compression using jpeg2000 and principal component analysis. IEEE Geosci. Remote Sens. Lett., 4: 201-205.

Farrell, M. and Mersereau, R.M., 2005. On the impact of PCA dimension reduction for hyperspectral detection of difficult targets. IEEE Geosci. Remote Sens. Lett., 2: 192-195.

Freire, S.L.M. and Ulrych, T.J., 1988. Application of singular value decomposition to vertical seismic profiling. Geophysics, 53: 778-785.

Gan, S., Wang, S., Chen, Y. and Chen, X., 2016a. Simultaneous-source separation using iterative seislet-frame thresholding. IEEE Geosci. Remote Sens. Lett., 13: 197-201.

Gan, S., Wang, S., Chen, Y., Chen, X., Huang, W. and Chen, H., 2016b. Compressive sensing for seismic data reconstruction via fast projection onto convex sets based on seislet transform. J. Appl. Geophys., 130: 194-208.

Gan, S., Wang, S., Chen, Y., Chen, X. and Xiang, K., 2016c. 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., 2016d. Velocity analysis of simultaneous-source data using high-resolution semblance-coping with the strong noise. Geophys. J. Internat., 204: 768-779.

Gan, S., Wang, S., Chen, Y., Zhang, Y. and Jin, Z., 2015. Dealiased seismic data interpolation using seislet transform with low-frequency constraint. IEEE Geosci. Remote Sens. Lett., 12: 2150-2154.

Huang, G., Zhou, B., Li, H. and Nobes, D.C., 2017a. Seismic traveltime inversion based on tomographic equation without integral terms. Comput. Geosci., 104: 29-34.

Huang, W., Wang, R., Chen, X., Chen, Y., 2017b. Double least squares projections method for signal estimation. IEEE Transact. Geosci. Remote Sens., 55: 4111-4129.

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

Huang, W., Wang, R., Li, H. and Chen, Y., 2017c. Unveiling the signals from extremely noisy microseismic data for high-resolution hydraulic fracturing monitoring. Scient. Rep., 7: 11996.

Huang, W., Wang, R., Yuan, Y., Gan, S. and Chen, Y., 2017d. Signal extraction using randomized-order multichannel singular spectrum analysis. Geophysics, 82: V59-V74.

Huang, W., Wang, R., Zhang, D., Zhou, Y., Yang, W. and Chen, Y., 2017e. Mathematical morphological filtering for linear noise attenuation of seismic data. Geophysics, 82: V369-V384.

Huang, W., Wang, R., Zu, S. and Chen, Y., 2017. Low-frequency noise attenuation in seismic and microseismic data using mathematical morphological filtering. Geophys. J. Internat., 211: 1318-1340.

Hyvarinen, A., Karhunen, J. and Oja, E., 2001. Independent Component Analysis. John Wiley & Sons, New York.

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

Li, H., Wang, R., Cao, S., Chen, Y., Tian, N. and Chen, X., 2016b. Weak signal detection using multiscale morphology in microseismic monitoring. J. Appl. Geophys., 133: 39-49.

Li, Q. and Gao, J., 2014. Application of seismic data stacking in time-frequency domain. IEEE Geosci. Remote Sens. Lett., 11: 1484-1488.

Li, Y., Li, Z., Zhang, K. and Lin, Y., 2016c. Frequency-domain full waveform inversion with rugged free surface based on variable grid finite-difference method. J. Seismic Explor., 25: 543-559.

Lin, H., Li, Y., Ma, H., Yang, B. and Dai, J., 2015. Matching-pursuit-based spatial-trace time-frequency peak filtering for seismic random noise attenuation. IEEE Geosci. Remote Sens. Lett., 12: 394-398.

Lindstrom, P., Chen, P. and Lee, E.J., 2016. Reducing disk storage of full-3D seismic waveform tomography (F3DT) through flossy online compression. Comput. Geosci., 93: 45-54.

Liu, G., Fomel, S. and Chen, X., 2011. Stacking angle-domain common-image gathers for normalization of illumination. Geophys. Prosp., 59: 244-255.

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

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

Liu, W., Cao, S. and Chen, Y., 2016b. Seismic time-frequency analysis via empirical wavelet transform. IEEE Geosci. Remote Sens. Lett., 13: 28-32.

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

Liu, W., Cao, S., Gan, S., Chen, Y., Zu, S. and Jin, Z., 2016d. One-step slope estimation for dealiased seismic data reconstruction via iterative seislet thresholding. IEEE Geosci. Remote Sens. Lett, 13: 1462-1466.
Liu, W., Cao, S., Liu, Y. and Chen, Y., 2016e. Synchrosqueezing transform and its applications in seismic data analysis. J. Seismic Explor., 25: 27-44.
Liu, W., Cao, S., Wang, Z., Kong, X. and Chen, Y., 2017. Spectral decomposition or hydrocarbon detection based on VMD and teager-kaiser energy. IEEE Geosci. Remote Sens. Lett., 14: 539-543.
Neelamani, R., Dickens, T.A. and Deffenbaugh, M., 2006. Stack-and-denoise: A new method to stack seismic datasets. Expanded Abstr., 76th Ann. Internat. SEG Mtg., New Orleans: 2827-2831.
Ren, C. and Tian, X., 2016. Prestack migration based on asymmetric wave-equation extrapolation. J. Seismic Explor., 25: 375-397.
Schoenberger, M., 1996. Optimum weighted stack for multiple suppression. Geophysics, 61: 891-901.
Shen, H., Yan, Y., Chen, C. and Zhang, B., 2016. Multiple-transient surface wave phase velocity analysis in expanded f-k domain and its application. J. Seismic Explor., 25: 299-319.
Siahsar, M.A.N., Abolghasemi, V. and Chen, Y., 2017a. Simultaneous denoising and interpolation of 2D seismic data using data-driven non-negative dictionary learning. Sign. Process. 141: 309-321.
Siahsar, M.A.N., Gholtashi, S., Kahoo, A.R., Chen, W. and Chen, Y., 2017b. Data-driven multi-task sparse dictionary learning for noise attenuation of 3D seismic data. Geophysics, 82: V385-V396.
Siahsar, M.A.N., Gholtashi, S., Olyaei, E., Chen, W. and Chen, Y., 2017c. Simultaneous denoising and interpolation of 3D seismic data via damped data-driven optimal singular value shrinkage. IEEE Geosci. Remote Sens. Lett., 14: 1086-1090.
Tian, Y., Li, Y. and Yang, B., 2014. Variable-eccentricity hyperbolic-trace TFPF for seismic random noise attenuation. IEEE Transact. Geosci. Remote Sens., 52: 6449-6458.
Wang, Y., Zhou, H., Chen, H. and Chen, Y., 2018. Adaptive stabilization for Q-compensated reverse time migration. Geophysics, 83: S15-S32.
Wang, Y., Zhou, H., Zu, S., Mao, W. and Chen, Y., 2017. Three-operator proximal splitting scheme for 3D seismic data reconstruction. IEEE Geosci. Remote Sens. Lett., 14: 1830-1834.
Wu, J., Wang, R., Chen, Y., Zhang, Y., Gan, S. and Zhou, C., 2016. Multiples attenuation using shaping regularization with seislet domain sparsity constraint. J. Seismic Explor., 25: 1-9.
Xie, J., Chen, W., Zhang, D., Zu, S. and Chen, Y., 2017. Application of principal component analysis in weighted stacking of seismic data. IEEE Geosci. Remote Sens. Lett., 14: 1213-1217.
Yang, W., Wang, R., Wu, J., Chen, Y., Gan, S. and Zhong, W., 2015. An efficient and effective common reflection surface stacking approach using local similarity and plane-wave flattening. J. Appl. Geophys., 117: 67-72.
Zhang, D., Chen, Y., Huang, W. and Gan, S., 2016a. Multi-step damped multichannel singular spectrum analysis for simultaneous reconstruction anddenoising of 3D seismic data. J. Geophys. Engin., 13: 704-720.
Zhang, D., Zhou, Y., Chen, H., Chen, W., Zu, S. and Chen, Y., 2017. Hybrid rank-sparsity constraint model for simultaneous reconstruction and denoising of 3D seismic data. Geophysics, 82: V351-V367.
Zhang, L., Wang, Y., Zheng, Y. and Chang, X., 2015. Deblending using a high-resolution Radon transform in a common midpoint domain. J. Geophys. Engin., 12: 167.

Zhang, Q., Chen, Y., Guan, H. and Wen, J., 2016b. Well-log constrained inversion for lithology characterization: a case study at the jz25-1 oil field, China. J. Seismic Explor., 25: 121-129.

Zhong, W., Chen, Y., Gan, S. and Yuan, J., 2016. L1/2 norm regularization for 3D seismic data interpolation. J. Seismic Explor., 25: 257-268.

Zhou, Y., Li, S., Xie, J., Zhang, D. and Chen, Y., 2017a. Sparse dictionary learning for seismic noise attenuation using a fast orthogonal matching pursuit algorithm. J. Seismic Explor., 26: 433-454.

Zhou, Y., Li, S., Zhang, D. and Chen, Y., 2018. Seismic noise attenuation using an online subspace tracking algorithm. Geophys. J. Internat., 212: 1072-1097.

Zhou, Y., Shi, C., Chen, H., Xie, J., Wu, G. and Chen, Y., 2017b. Spike-like blending noise attenuation using structural low-rank decomposition. IEEE Geosci. Remote Sens. Lett., 14: 1633-1637.

Zu, S., Zhou, H., Chen, Y., Pan, X., Gan, S. and Zhang, D., 2016a. Interpolating big gaps using inversion with slope constraint. IEEE Geosci. Remote Sens. Lett., 13: 1369-1373.

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

Zu, S., Zhou, H., Li, Q., Chen, H., Zhang, Q., Mao, W. and Chen, Y., 2017a. Shot-domain deblending using least-squares inversion. Geophysics, 82. V241-V256.

Zu, S., Zhou, H., Mao, W., Zhang, D., Li, C., Pan, X. and Chen, Y., 2017b. Iterative deblending of simultaneous-source data using a coherency-pass shaping operator. Geophys. J. Internat., 211: 541-557.