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Multichannel deconvolution based on spatial structurally constraint and its applications

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Abstract: Traditional deconvolution methods based on single-channel inversion do not consider the spatial structural relation between channels, and hence, they yield high-resolution results with the existing transverse inconsistency or discontinuity. Therefore, in this study, the local dip angle was used to obtain the structural information and construct the spatial structurally constraint operator. This operator is then introduced into multichannel deconvolution as a regularization operator to improve the resolution and maintain the transverse continuity of seismic data. Model tests and actual seismic data processing have demonstrated the effectiveness and practicability of this method.
Keywords: transverse constraint, spatial structurally constraint operator, multichannel deconvolution

Introduction

The underground medium is stratified; hence, its seismic profile shows good transverse continuity. Most traditional deconvolution methods are based on single channels, and the results of each channel are only related to that channel. The traditional single-channel inversion methods neglect the spatial structure relationship among the channels, and hence, the results of these methods often produce transverse discontinuities. Multichannel deconvolution or inversion methods with transverse constraints have been proposed to overcome the problem of poor transverse continuity of inversion results.

Zhang Hongbing and Yang Changchun (2004) added a potential function to the objective function of inversion and improved the inversion result by adjusting the weight coefficient, thereby improving the convergence speed of inversion. Zhang Hongbing (2005) added another prior information on the basis of the potential function, thereby improving the resolution and reducing the multiple solutions of inversion results. Yuan (2012) proposed suppressing random noise and adopted an isolated noise method by taking the longitudinal and transverse first-order derivatives of seismic data as sparse constraint terms in the inversion process, achieving good denoising effects. Zhang (2013) proposed a multichannel basis pursuit inversion method with transverse constraints and adopted a z-type spatial derivative operator on the transverse constraints to improve the transverse consistency of inversion results. Kazemi and Sacchi (2014) proposed a sparse-source multichannel blind deconvolution (SMBD) method; this method assumes that the reflection coefficient sequence is sparse by solving a uniform system of equations to get a sparse solution, which can withstand moderate noise and does not require the prior information of wavelet but need considerable calculation. Yuan (2015) proposed a multichannel inversion method for wave impedance inversion in the transform domain; this method realized simultaneous multichannel impedance inversion by imposing a constraint term on the seismic

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data of dimensionality reduction and solved the problem of lateral discontinuity in the single-channel inversion method. Yuan (2016) proposed a stable inversion-based multichannel compensation method; this method performs multichannel simultaneous inversion by calculating the minimum of the objective function of the reflection coefficient in the F–K domain and thus preserves the transverse continuity of the in-phase axis better than the conventional single-channel method. Nosefilho (2016) proposed a fast algorithm for the improved SMBD method based on minimum entropy deconvolution. This method minimizes the normalized mixed L1 and L2 norm objective functions by designing a deconvolution filter with little calculation and high efficiency. Therefore, one lateral constraint method is based on the model constraint class. The lateral constraint operator of the model-driven multichannel inversion method is fixed. Since inversion results are easily affected by the model structure, different models deliver highly different results. The other method is to transform seismic data to a specific domain by applying a lateral constraint, but this method involves much computation and suffers from high instability in the inversion iteration. This paper introduces a spatial structurally constraint operator as the constraint condition. This operator is entirely data-driven and can maintain transverse continuity while improving the resolution of seismic records.

Theory

Conventional sparse deconvolution method

A seismic signal can be considered as the convolution of the seismic wavelet and reflection coefficient (Yilmaz, 2001):

$$s(t) = w(t) * r(t), \tag{1}$$

where $w(t)$ is the seismic wavelet, $r(t)$ is the reflection coefficient, $s(t)$ is a seismic record, and * is a convolution operator.

Actual seismic data often contain much noise, as expressed in equation (1.2):

$$d(t) = s(t) + n(t), \tag{2}$$

where $d(t)$ is the actual seismic record, and $n(t)$ is random noise.

The objective function of sparse deconvolution can be obtained according to the Bayesian principle (Taylor, 1979):

$$J = \left\| \mathbf{Wr} - \mathbf{d} \right\|^2 + \mu_1 \left\| \mathbf{r} \right\|_1, \tag{3}$$

where W is the wavelet convolution matrix. Further, μ_1 is the regularization parameter, and the second term is the sparse constraint term. We can select the Cauchy constraint, sech distribution, Huber distribution, modified Cauchy constraint, etc. In this study, the modified Cauchy constraint was selected. This constraint provides good resolution even for small reflection coefficients.

The optimization problem of the objective function (Eq. 1.3) is nonlinear and can be solved by the conjugate gradient and reweighted iterative methods.

Construction of a spatial structurally constraint operator

The key to deriving a construction-oriented operator is calculating the local dip attribute of the seismic-wave event axis. To avoid the influence of noise, Fomel (2006) proposed that the Hilbert transform should replace the derivative operation to obtain the local inclination attribute, as shown below:

$$\sigma = -\frac{H_{HTx}}{H_{HTy} + \xi}, \tag{4}$$

where H_{HTx} and H_{HTy} are the components of the Hilbert transform in the time and space directions, respectively, and ξ is a minimal nonzero constant. In the actual calculation process, the local dip attribute of the codirectional axis of the seismic wave is obtained by calculating the components of the Hilbert transform in the time and space directions to reduce the amplification effect of the high-frequency noise caused by the direct derivation operation.

After the local inclination σ is obtained, the prediction factor of each trace $Q_{i,j}(\sigma_i)$ can be calculated. Subsequently, the spatial structurally constraint operator can be obtained as T = 1/D, where D can be expressed as follows:

$$D = \begin{bmatrix} I & 0 & \cdots & 0 \\ -Q_{1,2}(\sigma_1) & & & \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & -Q_{N-1,N}(\sigma_{N-1}) & I \end{bmatrix}, \tag{5}$$

where I is the identity matrix, σ_i is the local inclination, and $Q_{i,j}(\sigma_i)$ is the predictor of channels I and J.

Laterally constrained multichannel deconvolution

For seismic records, the structurally guided operator T is added to the inversion objective function as a transverse constraint, and the modified Cauchy constraint is selected as the longitudinal constraint in the multichannel deconvolution method. The final objective function is obtained as follows:

$$J = \left\|\mathbf{Wr} - \mathbf{d}\right\|^2 + \mu_1 \left\|\mathbf{r}\right\|_1 + \mu_2 \left\|T\mathbf{Wr}\right\|^2, \tag{6}$$

where μ_2 is the regularization term parameter that controls transverse continuity.

In this study, we used the split Bregman optimization algorithm to solve the objective function (6). The iterative solution process can be divided into the following three steps:

(1) Solving linear problems by the conjugate gradient method

$$r^{k+1} = \arg\min_m \| d - Wr \|_2^2 + \frac{\lambda}{2} \| x^k - m - b_x^k \|_2^2 + \mu_x \| TWr \|_2^2, \tag{7}$$

(2) Using a fast soft threshold algorithm to solve nonlinear problems

$$x^{k+1} = \arg\min_x \mu_z \| x \|_1 + \frac{\lambda}{2} \| x - r^{k+1} - b_x^k \|_2^2, \tag{8}$$

(3) Updating auxiliary variables

$$b_x^{k+1} = b_x^k + r^{k+1} - x^{k+1}, \tag{9}$$

where, k is the number of iterations. Initially, variables x^k and b_x^k are zero, and λ is the regularization factor, generally set to one.

Experimental analysis

To verify the effectiveness of this method, we designed a reflection coefficient model, as shown in Figure 1 (a). The seismic records shown in Figure 1 (b) were obtained by convoluting the model with a zero-phase wavelet with a dominant frequency of 30Hz and a sampling interval of 1 ms. Figure 2 (a) shows the seismic record with random noise with a signal-to-noise ratio (SNR) of 5, as in Figure 1 (b). Figure 2 (b) shows the deconvolution results obtained by the modified Cauchy-constrained single multichannel deconvolution method. Figure 3 (a) shows the spatial structurally constraint

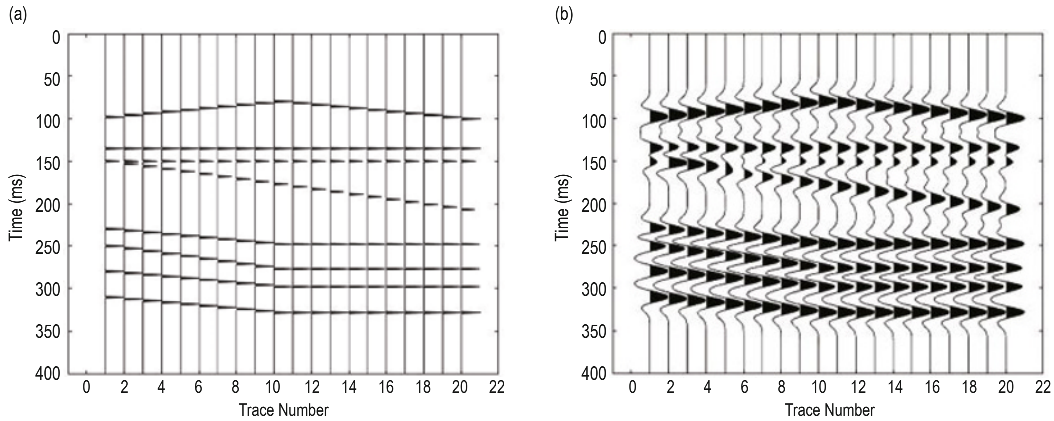

Fig. 1 (a) Reflectivity model, (b) synthetic, clean seismic data.

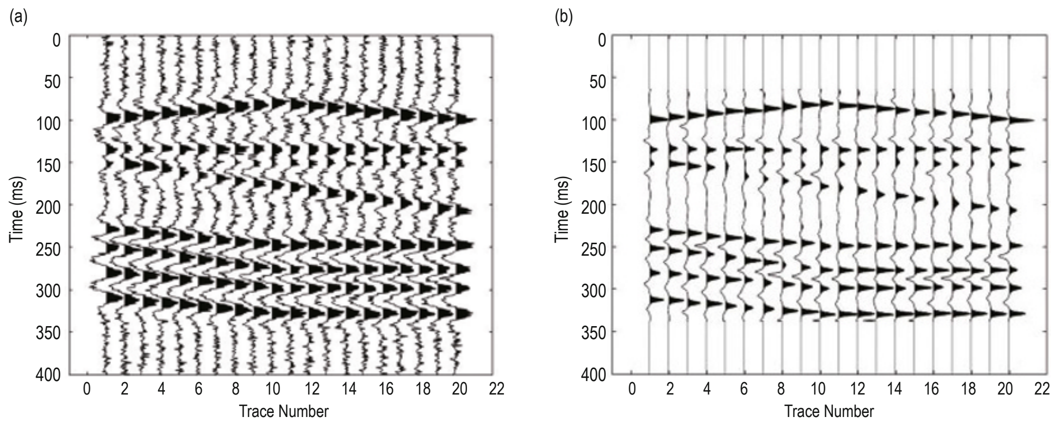

Fig. 2 (a) Noisy data (signal-to-noise ratio, S/N = 5), (b) deconvolution result obtained by modified Cauchy deconvolution.

operator of the noisy data, and Figure 3 (b) shows the multichannel deconvolution results obtained in this study. A comparison of the results in Figure 3 (b) and Figure 2 (b) shows that although the modified Cauchy-constrained single-channel deconvolution can drastically improve the resolution of seismic records, it removes a part of the effective signal, and the in-phase axis shows jitters and is discontinuous in the transverse direction. The method proposed herein achieves clean results with good transverse continuity.

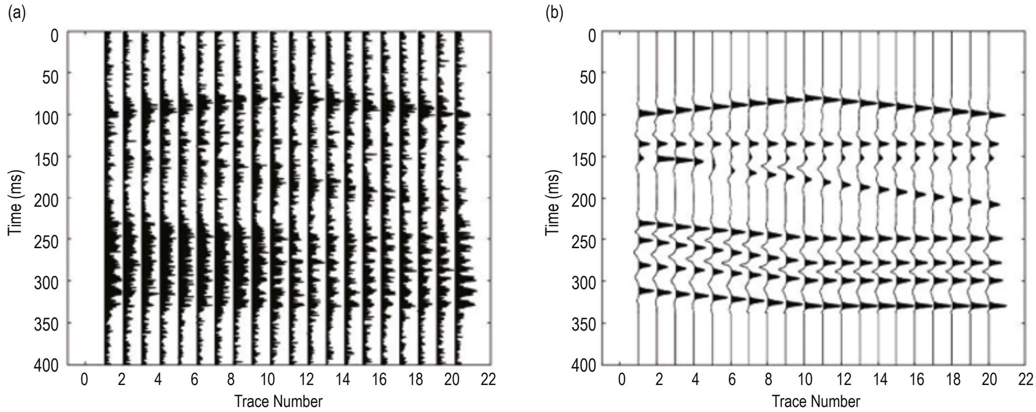

Fig. 3 (a) Spatial structurally constraint operator (from Figure 2 (a), (b) deconvolution result obtained by the multitrace deconvolution method shown in Figure 2 (a).

Applications

Figure 4 (a) shows the actual mountain seismic data of the Sichuan Basin, with a dominant frequency band of 20–35 hz (the blue curve in Figure 5 (b)). Figure 4 (b) shows the results of the modified Cauchy-constrained deconvolution, and the corresponding spectrum analysis result (the red curve) is shown in Figure 5 (b). Figure 5 (a) shows the result of multichannel deconvolution, and Figure 5 (b) shows the corresponding spectrum analysis results (the orange curve). A comparison of the spectrum analysis results shows that both methods effectively improve the seismic data resolution, making the fine structures of seismic data clearer. However, the comparison of the results of the two deconvolution methods also reveals that the SNR of the modified Cauchy-constrained deconvolution method is low, and the continuity of the in-phase axis at the thin interbedding is extremely poor. However, the results

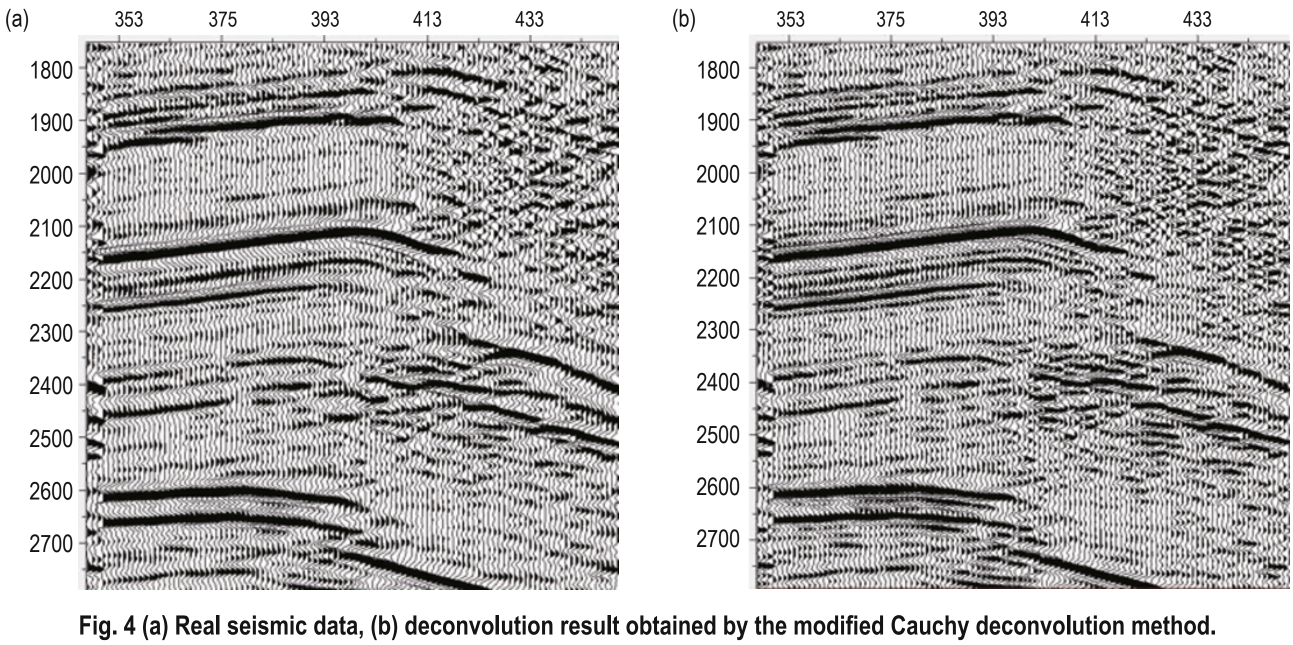

Fig. 4 (a) Real seismic data, (b) deconvolution result obtained by the modified Cauchy deconvolution method.

of the multichannel deconvolution method proposed herein show a high SNR for the whole profile, and the transverse continuity of the in-phase axis is better and has a higher lateral resolution than that obtained with the other method.

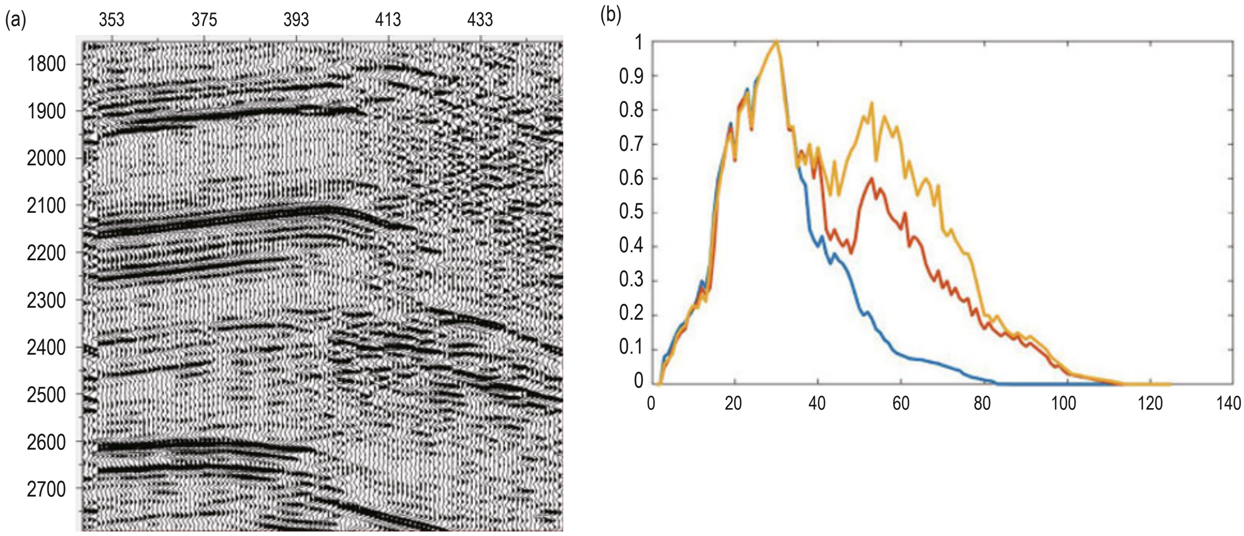

Fig. 5 (a) Multichannel deconvolution result, (b) spectrum analysis comparison (blue: real seismic data; red: results corresponding to Figure 4 (b); orange: results corresponding to Figure 5 (a)).

Conclusions

The conventional nonlinear deconvolution method is based on single-channel inversion. When the SNR of seismic data is high, good high-resolution results can be obtained. However, when the seismic data have low SNR, the conventional method becomes very unstable, and the deconvolution result is prone to transverse discontinuity. The existing multichannel deconvolution methods are mainly divided into two types: model-driven and data-driven methods. Data-driven methods have better adaptability than model-driven ones, and hence, they provide better deconvolution results than those of model-driven methods. The multichannel deconvolution method proposed herein is a data-driven method that uses a spatial structurally constraint operator obtained from the data as the transverse constraint term. The use of this operator not only improves the seismic data resolution but also the transverse continuity of the seismic profile.

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