MULTIPLES ATTENUATION IN THE PRESENCE OF BLENDING NOISE

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ABSTRACT

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Simultaneous-source acquisition is a modern seismic acquisition breakthrough that greatly increases the acquisition efficiency and spatial sampling ratio. Because of the extremely strong blending interference caused by simultaneous shooting, most traditional seismic data processing and imaging procedures need to be modified to deal with the noise issue in the new acquisition paradigm. For multiples attenuation, two common ways exist for processing the blended data, i.e., 1) multiples attenuation can be implemented on deblended data in a conventional way and 2) new algorithms for multiples attenuation can be developed to remove multiples directly from the blended data. In this paper, we propose a multi-dip seislet frame based sparse inversion algorithm to iteratively remove multiples directly from blended data. The multiples attenuation problem can be formulated as an inverse problem with regularization applied on both primaries and multiples components. For the noise issue, we propose to use a robust dip estimation approach that is based on velocity-slope transformation. Instead of calculating the local slope using the plane-wave destruction (PWD) based method, we first apply NMO-based velocity analysis approach and obtain NMO velocities for multi-dip components that correspond to different orders of multiples, then a fairly accurate slope estimation can be obtained using the velocity-slope conversion equation. We use both synthetic and field data examples to demonstrate the performance of the proposed algorithm framework.

KEY WORDS: multiples attenuation, sparse inversion, slope estimation,
simultaneous-source acquisition.

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INTRODUCTION

Simultaneous-source acquisition provides us larger freedom in acquiring the seismic data (Beasley et al., 1998; Hampson et al., 2008; Berkhout, 2008; Abma and Yan, 2009; Kim et al., 2009; Abma et al., 2010; Borselen et al., 2012; Beasley et al., 2012; Alexander et al., 2013; Abma, 2014; Abma et al., 2015; Chen et al., 2017b; Zhou, 2017) and helps the field crews enjoy the two-folds benefit regarding both acquisition cost and shot sampling density. No limit on temporal or spatial interval size exists in the newly developed blended acquisition. Thus, the field acquisition efficiency has been increased tremendously while the spatial sampling is dense enough to avoid the aliasing issue. However, the new technology sets a greater challenge to prepare the seismic data that is noise-free by separating simultaneous sources, which is also known as deblending.

To date, algorithms in the literature have employed coherency-based FK filtering (Mahdad, 2012), median-based filtering (Huo et al., 2012; Gan et al., 2016c), sparsity-based methods using Radon transforms (Xue et al., 2014; Ibrahim and Sacchi, 2014, 2015; Xue et al., 2016b; Sun and Wang, 2016; Xue et al., 2017), curvelets (Cand_es et al., 2006; Neelamani et al., 2008; Lin and Herrmann, 2009; Liu et al., 2015a, 2016c; Zu et al., 2016a,b, 2017b), shearlet transform (Kong et al., 2016; Liu et al., 2016a), seislets (Chen et al., 2014; Gan et al., 2015; Chen, 2015; Gan et al., 2016b,a), different types of wavelet transforms (e.g., physical, synchrosqueezing, empirical wavelet transforms, etc.) (Donoho and Johnstone, 1994; Zhang and Ulrych, 2003; Gao et al., 2006; Liu et al., 2016b,d), or adaptively learned sparse dictionaries (Chen, 2017; Siahsar et al., 2017a,b,c). Another approach is to use rank-reduction techniques (Cheng and Sacchi, 2015; Xue et al., 2016a), exploiting the fact that blending noise increases the rank of certain data subsets. The filtering methods simply treat the deblending problem as a noise attenuation problem (Huo et al., 2012; Aminzadeh et al., 2013; Djarfour et al., 2014; Chen and Fomel, 2015; Huang et al., 2016; Chen et al., 2016a; Huang et al., 2017c,b,d,e; Chen et al., 2016b, 2017c). The inversion methods formulate the deblending problem as a regularized inverse problem and use iterative solvers to tackle the inverse problem (Wapenaar et al., 2012; Qu et al., 2014, 2015, 2016; Zu et al., 2017a).

Deblending utilizes the first-separation and second-processing strategy and is the most straightforward way to deal with the strong noise in simultaneous source data (Zhou, 2017; Zhou et al., 2017). The goal is to attenuate the interference before passing the data into the traditional seismic data processing workflow. The more advanced way for dealing with the noise of simultaneous source data is to completely overlook the interference and to focus only on developing robust seismic imaging and inversion algorithms that are specifically designed for extremely noisy data (Guitton and Daz, 2012; Chen et al., 2015; Gan et al., 2016d; Xue et al., 2016c; Chen et al., 2017d). Two main challenges in designing the direct imaging algorithms are (1) anti-noise constraint during least-squares based iterative migration and (2) building an acceptable macro subsurface velocity model (Lindstrom et al., 2016; Huang et al., 2017a). The former, again, requires a robust denoising operator that can attenuate migration artifacts in the image without damaging the useful seismic reflection events. The latter, however, is extremely difficult to handle and currently is seldom investigated.

Multiples are multiplicative events seen in seismic profiles, which undergo more than one reflections. Instead of being incoherent along the spatial direction like random noise, the multiples are coherent and behave nearly the same as the primary reflections, which makes the removal of them very difficult using simple signal processing methods (Wu et al., 2016; Chen et al., 2017a). Traditional multiples attenuation algorithms can be grouped into two types. A wave-equation-based multiples attenuation method usually consists of two steps: multiple prediction and adaptive subtraction (Verschuur et al., 1992; Huo and Wang, 2009). The difficulty of this type of demultiple approaches lays in both parts: (1) how to get a precise prediction for all the types of multiples and (2) how to design an optimal matching filter (MF) for the subtraction. Based on this type of approaches, there have been many approaches for improving the attenuation of multiples, either enhancing the prediction or enhancing adaptive subtraction (Foster and Mosher, 1992; Admundsen et al., 2001; Huo and Wang, 2009; Fomel, 2009; Donno, 2011). The inverse scattering series (ISS) based demultiple approaches predict the amplitude and phase of free surface multiples at all offsets, and do not require a Radon transform or adaptive subtraction step and can eliminate the multiples in the presence of interfering events (Carvalho, 1992; Weglein et al., 2003; Weglein, 2013).

The multiples attenuation problem in the presence of blending noise has seldom been investigated in the literature until Ma et al. (2016). Considering the similarity between multiples and primaries in spatial coherence, the straightforward way to deal with multiples is by first deblending and second demultipling. Ma et al. (2016) instead proposed a first demultipling and second deblending strategy. Ma et al. (2016) extended surface-related multiple elimination (SRME) theory, in which free-surface multiples of the blended data can be predicted by a multidimensional convolution of the seismic data with the inverse of the blending operator. An adaptive subtraction procedure similar to that used in conventional SRME is then applied to obtain the blended primaries. The method proposed in Ma et al. (2016) cannot separate the blending noise and multiples, the results from their algorithm are two separated datasets both with strong blending noise, which requires a further deblending step. In this paper, we propose a direct multiples attenuation algorithm to remove multiples directly from the blended data via a new sparse inversion algorithm. Apart from the rejected multiples, the blending noise can also be rejected due to the sparse constraint applied during the inversion.

We organize the paper as follows: we first introduce the multi-dip seislet transform constrained sparse inversion framework for removing multiples of different orders (and with different local slopes). Then, a sparsity comparison will be given to support the compressive capability of the seislet transform. Next, to deal with the difficulty of slope estimation caused by the intense blending noise, the robust slope estimation strategy from velocity analysis is introduced after the multi-dip seislet constrained method. We use both synthetic and field data examples to demonstrate the performance of the algorithm in rejecting both multiples and blending noise. We draw some key conclusions at the end of the paper.

THEORY

Multiples attenuation by sparse inversion

Suppose the seismic data is composed of M components each with the primary reflections or multiples of different orders. The recorded data can be formulated as (Wu et al., 2016)

$$\mathbf{d} = \Gamma \sum_{i=1}^{M} \mathbf{m}_i \quad , \tag{1}$$

where $\mathbf{m}_i$ is the i-th component, and Γ is a blending operator that blends different shot records onto one shot record (Zhou, 2017).

We can use the least-squares method with a regularization term to transform it to an optimization problem:

$$J = \frac{1}{2}\left\| \mathbf{d} - \Gamma \sum_{i=1}^{M} \mathbf{m}_i \right\|_2^2 + \boldsymbol{\varepsilon}^2 \mathbf{R}\left(\sum_{i=1}^{M} \mathbf{m}_i \right) \quad , \tag{2}$$

where $\mathbf{R}$ is a regularization term. $\|\cdot\|_2$ denotes the L_2 norm of an input vector.

Given the local slope corresponding to mi, the equation with sparse constraint in the seislet frame domain can be can be expressed as

$$J = \frac{1}{2}\left\| \mathbf{d} - \Gamma \sum_{i=1}^{M} \mathbf{m}_i \right\|_2^2 + \boldsymbol{\varepsilon}^2 \sum_{i=1}^{M} \|\mathbf{A}_i \mathbf{m}_i\|_1 \quad , \tag{3}$$

where $\mathbf{A}_i$ is the seislet transform for i-th component $\|\cdot\|_1$ denotes the L_1 norm of an input vector.

A projection-onto-convex-sets (POCS) solver can be used to solve eq. (3):

$$\mathbf{m}_i{}^{n+1} = C_i\left[\mathbf{m}_i{}^{n} + \lambda\Gamma^H\left[\mathbf{d} - \Gamma\sum_{i=1}^{M}\mathbf{m}_i\right]\right] \quad , \tag{4}$$

where C_i is a soft-thresholding operator in the seislet frame domain:

$$C_i = A_i^{-1}\mathbf{T}_\tau\mathbf{A}_i \quad . \tag{5}$$

λ is the model update length, which is usually chosen as $1/N$ and N is the number of simultaneous sources. A_i^{-1} denotes inverse transform. $\mathbf{T}_\tau$ denotes the soft-thresholding operator with an input threshold value τ . In this paper, we use an intelligent threshold value selection strategy called percentile thresholding. We preserve a constant percentage of the largest coefficients to achieve the thresholding. Thus, the threshold value τ is intelligently adjusted by the percentage we use. Generally, we select a percentage less than 5% to reject the small-amplitude coefficients.

Iterative deblending based on seislet domain sparsity constraint

The sparse inversion based deblending method requires that the seismic data is sufficiently sparse in the transform domain. The commonly used sparse transform includes the curvelet transform, Radon transform, regular Fourier transform, wavelet transform. In this paper, we propose to utilize the seislet transform to regularize the model.

The seislet transform is based on the second-generation wavelet transform and thus it can be implemented sufficiently. It constructs the forward transform by iteratively predicting and subtracting between the odd and even traces:

- Finding the difference between odd traces and predicted odd traces (from the even traces)

  $$\mathrm{r} = \mathrm{o} - \mathrm{P}[\mathrm{e}] \quad . \tag{6}$$

  where o denotes the odd trace, e denotes the even trace, r denotes the difference, and P is the predicting operator.

- Updating the even traces by

  $$\mathrm{c} = \mathrm{e} + \mathrm{U}[\mathrm{r}] \quad . \tag{7}$$

  where c denotes the updated trace, and U is the updating operator.

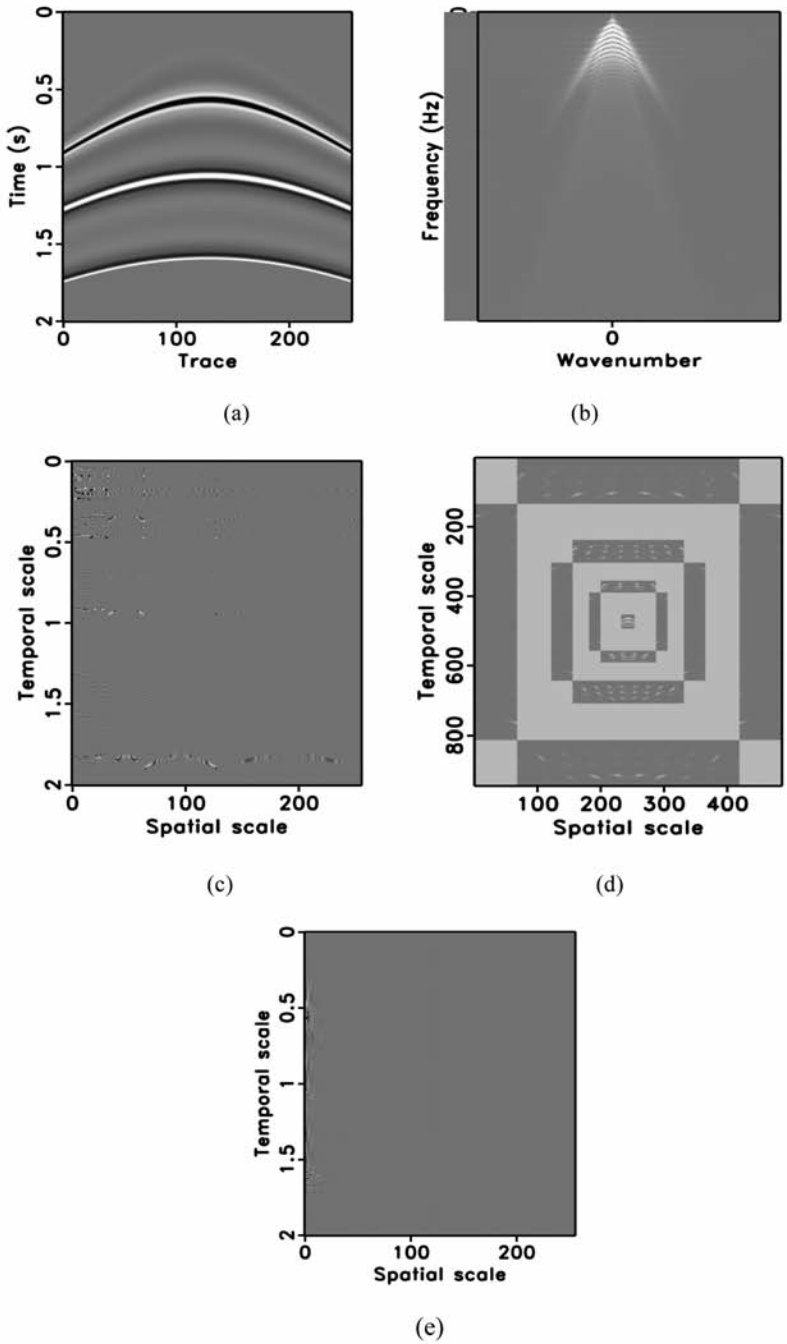


Fig. 1. (a) Simple seismic data with hyperbolic events. (b) FK spectrum. (c) Wavelet domain. (d) Curvelet domain. (e) Seislet domain.

To demonstrate the better performance of seislet transform when used to constrain the model, we conduct a sparsity comparison. Fig. 1 shows a comparison between different sparse transforms. Fig. 1a shows the synthetic data, which contains three hyperbolic events. Figs. 1b, 1c, 1d, and 1e show the sparse domains of regular Fourier transform, wavelet transform, curvelet transform, and seislet transform, respectively. Fig. 2 shows the coefficients decaying diagrams of the four sparse transforms. We plot the diagrams by sorting the coefficients (in terms of amplitude) in different domains into 1D vectors and plot the normalized vectors. The faster the diagram decays, the sparser the corresponding transform is. It is obvious that the diagram of the seislet transform decays fastest, which indicates that the seislet transform domain is the sparsest.

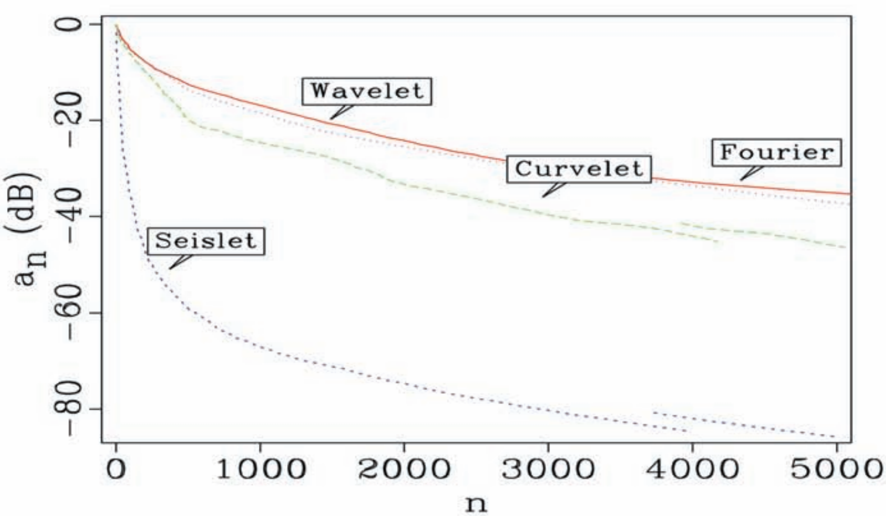


Fig. 2. Coefficients decaying diagrams.

Robust slope estimation

We follow the velocity-slope transformation given by Liu et al. (2015b):

$$\sigma(t,x) = \frac{x}{t(x)v^2(t_0,x)} \quad , \tag{8}$$

where t_0 is the zero-offset traveltime, $t(x)$ the traveltime recorded at offset x, $v^2(t_0)$ is the NMO velocity, σ denotes the local slope. Eq. (8) can be derived straightforwardly from the hyperbolic approximation of traveltime in common-midpoint domain:

$$t(x) = \sqrt{t_0^2 + \frac{x^2}{v^2(t_0)}} \quad . \tag{9}$$

Taking the derivative of eq. (9) with respect to variable x: $\sigma = dt/dx$, we arrive at eq. (8). When the dipping components in the seismic gather are all corresponding to multiple reflections of different orders, eq. (8) can be used to obtain slope fields corresponding to different multiples by substituting v and t_0 with the corresponding v_{mul} and t_{mul} picked from the NMO-based velocity spectra. More importantly, the advantage of the velocity-slope conversion is that NMO-based velocity analysis is relatively robust to the blending noise in the raw seismic data. However, directly slope estimation from the plane-wave destruction (PWD) algorithm (Fomel, 2002) is much more sensitive to the input noise level. We will demonstrate the robust performance of the velocity-slope estimation when discussing the performance of numerical examples. It is worth mentioning that the robust slope estimation from velocity-slope conversion works only in the CMP gathers. When the multi-dip components have much contradicting dips, other methods (although not robust enough), e.g., the methods used in Gan et al. (2016b), need to substitute the presented slope estimation method. We also admit that a flexible and robust multi-dip slope estimation algorithm is a topic that is worth being investigated, which can make the iterative seislet frame inversion based deblending algorithm work better.

EXAMPLES

In this section, we will use one synthetic and one field data example to test the performance of the proposed algorithm in realistic situations. Fig. 3a shows the unblended synthetic data that contains multiples of different orders. Fig. 3b shows the blended data, where the useful reflections and multiples are masked by strong blending interference. NMO-based velocity spectrum of the blended data is shown in Fig. 4. The peaks on the spectrum correspond to multiples of different orders. The black strings on the top of the spectrum denote the picked velocities for different components.

Figs. 5 show the slopes obtained from the velocity-slope conversion. The resulting slopes are very smooth and are not affected by the strong blending interference. Then, we applied the POCS based iterative framework. Each dipping component is constrained by seislet transform of a specific slope field. Figs. 6a-6d show the first, second, third, and fourth decomposed component from the blended data. Figs. 6b-6d correspond to the multiples of first order, second order and third order.

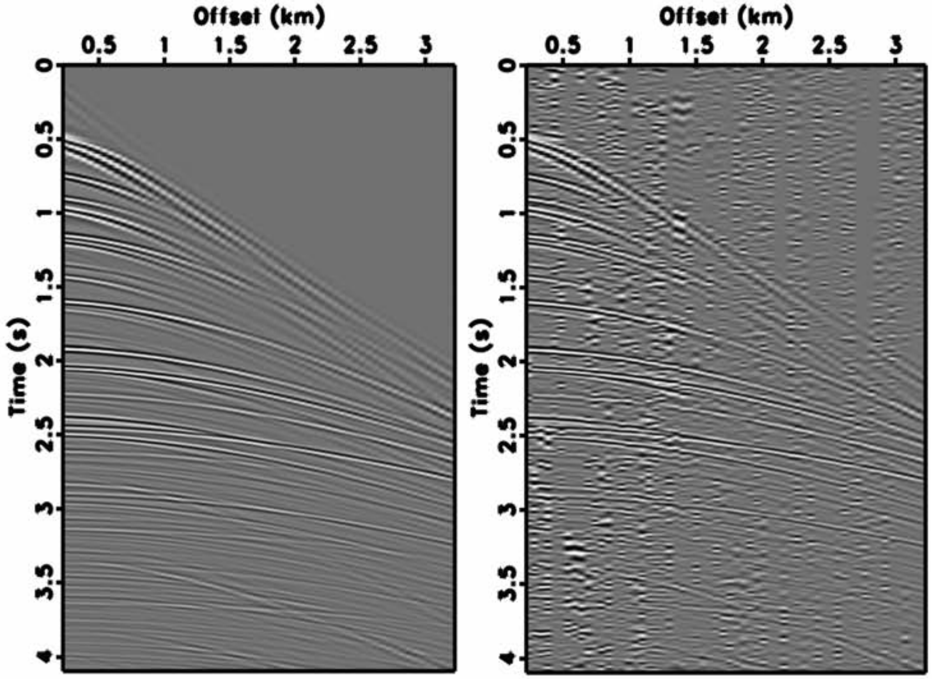


Fig. 3. Synthetic example. (a) Unblended data containing multiples of different orders. (b) Blended data with strong blending interference.

We then validate the single-slope property of each decomposed component by applying the NMO-based velocity analysis to each decomposed component. Figs. 7a-7d show the velocity spectra of the first, second, third, fourth component, respectively. The comparison of velocity spectra confirms that each component is pure-mode and all multiples are removed during the inversion.

Finally, we apply the proposed algorithm to a marine field dataset. The field data containing multiples and blending noise is shown in Fig. 8. In this example, we simply use M = 2 to decompose the data into primaries and multiples. The demultipled result and the corresponding removed multiples are shown in Figs. 9a and 9b. Figs. 10a and 10b show the velocity spectra corresponding to the primaries and multiples.

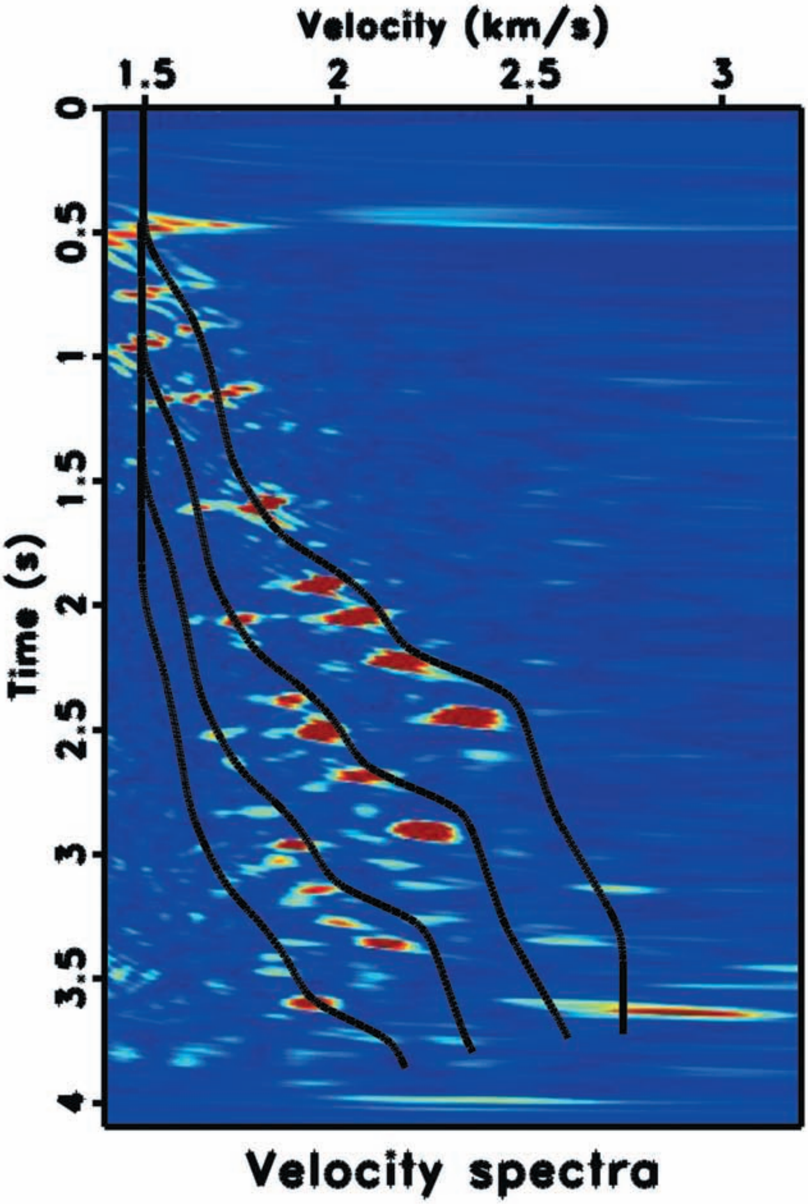


Fig. 4. Velocity spectrum of the blended data.

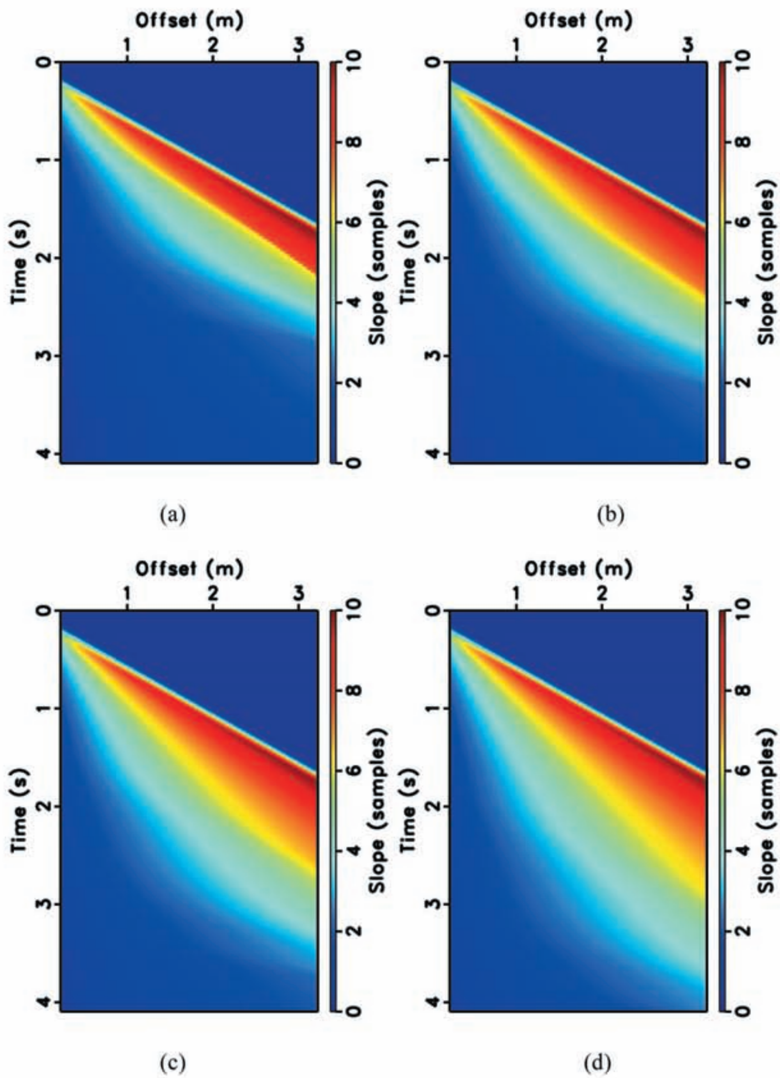


Fig. 5. Slopes converted from the velocity spectrum of blended data. (a) Local slope of the first component. (b) Local slope of the second component. (c) Local slope of the third component. (d) Local slope of the fourth component.

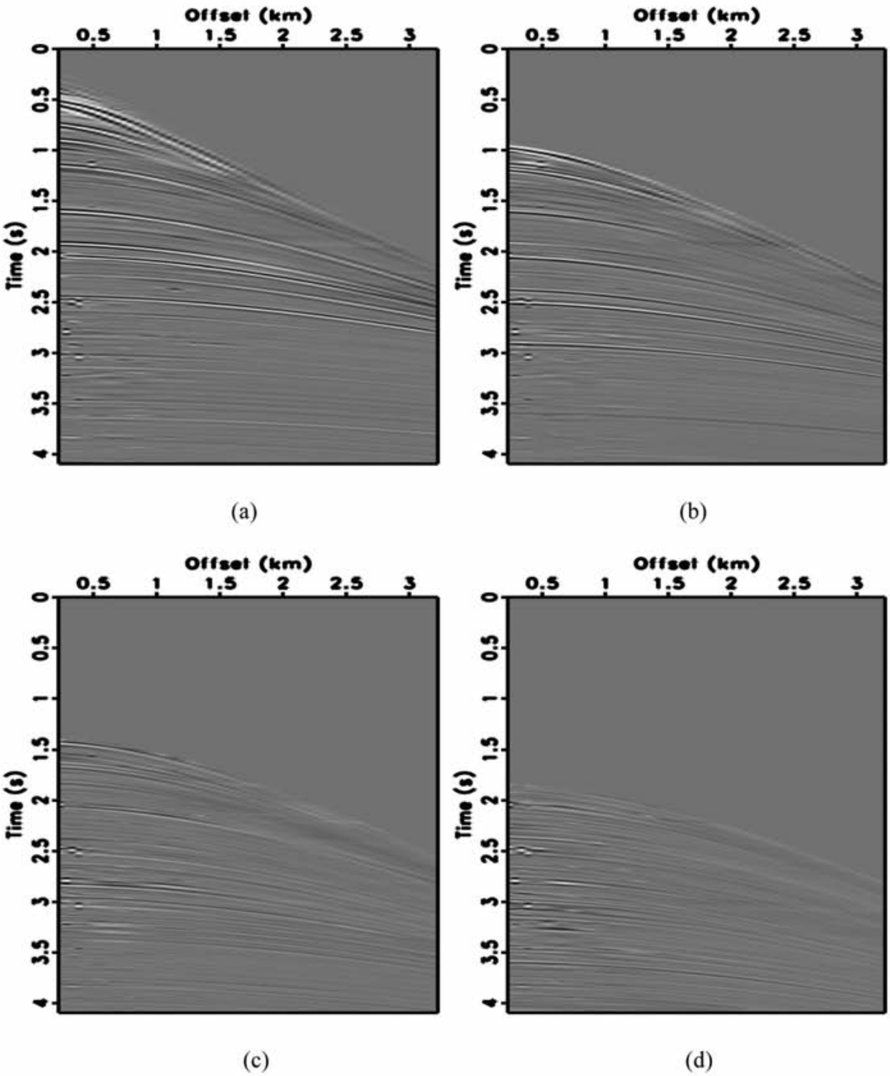


Fig. 6. Decomposed components from the blended data. (a) First component. (b) Second component. (c) Third component. (d) Fourth component. The second to fourth components correspond to multiples of different orders.

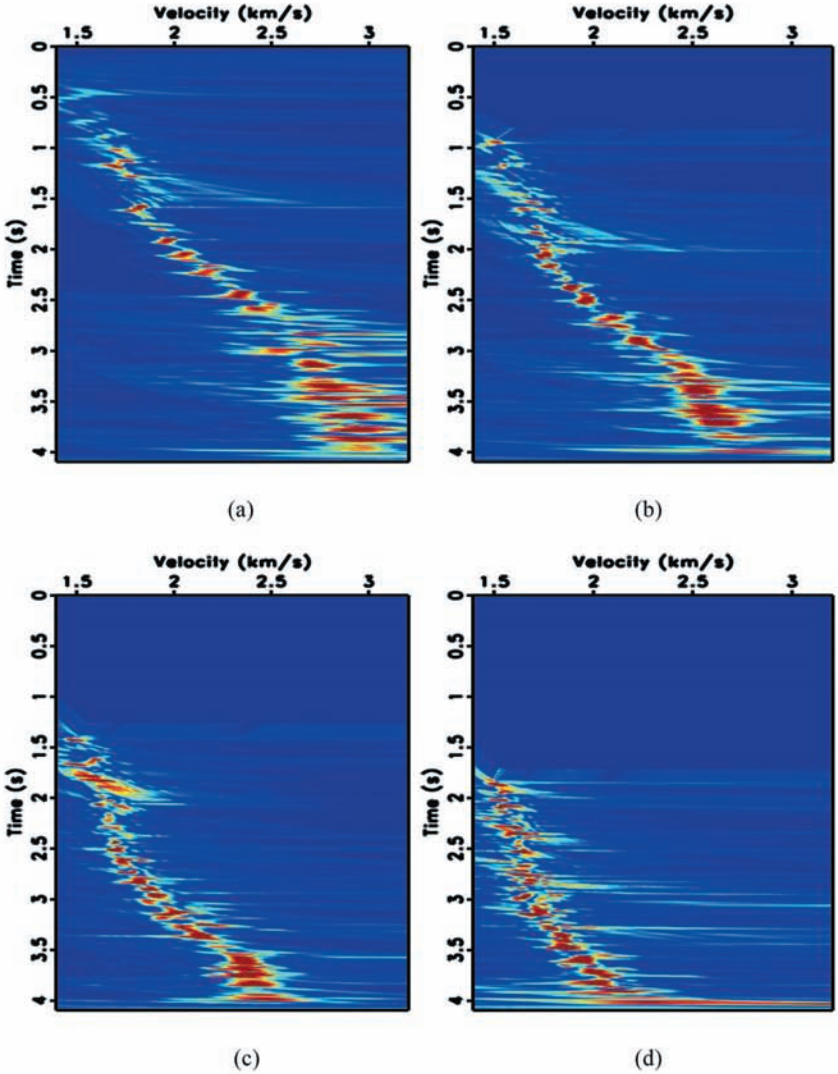


Fig. 7. (a) Velocity spectrum of the first component. (b) Velocity spectrum of the second component. (c) Velocity spectrum of the third component. (d) Velocity spectrum of the fourth component. Note that the velocity spectrum comparison confirms the effectiveness of the proposed method in rejecting multiples.

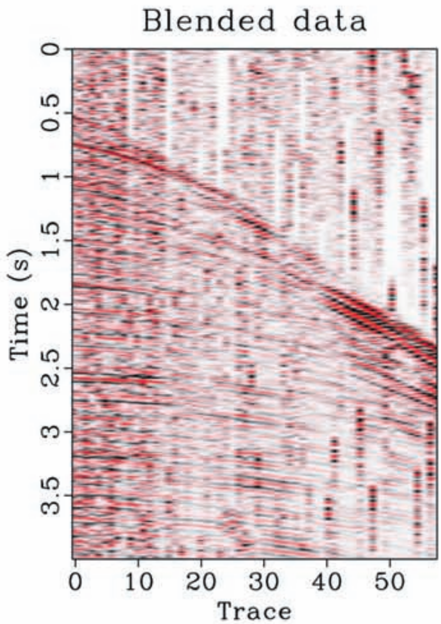
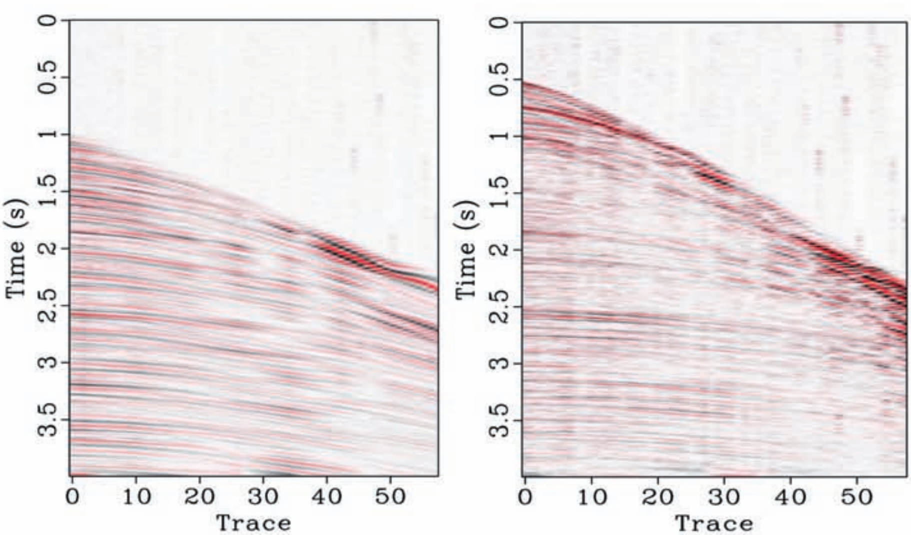
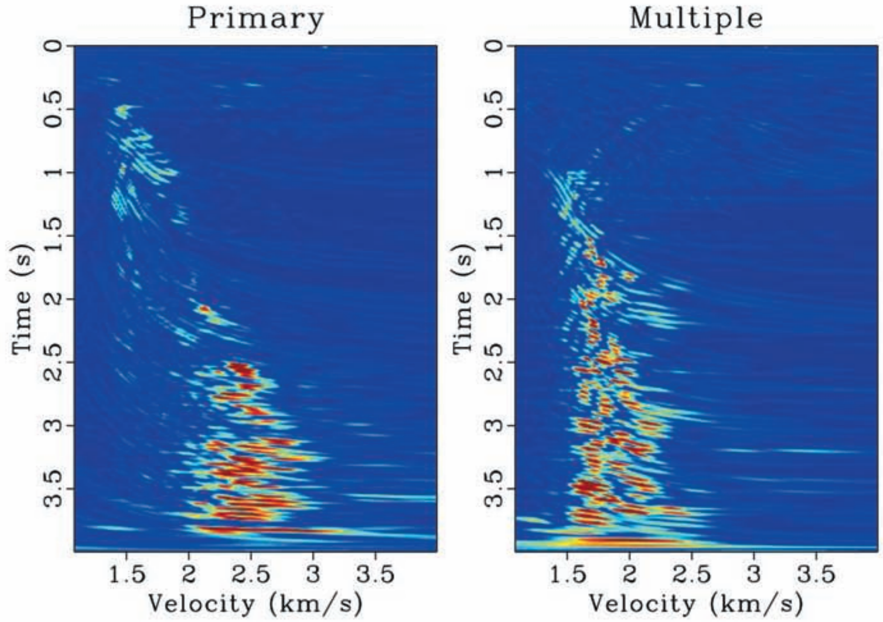


Fig. 8. Marine field data containing multiples and blending noise.



(a) (b)

Fig. 9. (a) Demultipled result. (b) Removed multiples.



(a) (b)

Fig. 10. Velocity spectra of (a) demultipled result and (b) removed multiples.

CONCLUSIONS

Multiples attenuation in the presence of blending noise can be formulated as an inverse problem, which can be solved by sparsity regularized inversion based on the projection onto convex sets (POCS) framework. The seislet transform has a better compression capability than the state-of-the-art sparse transforms and is suitable for constraining the primaries and multiples of different orders during iterative inversion. In the paper, the multi-dip problem caused by the morphological difference between primaries and multiples and the inaccurate slope estimation problem caused by the blending interference have been solved based on the multi-dip seislet frame method and the velocity-slope conversion. The synthetic example shows that normal moveout (NMO) based velocity analysis is robust in blended data. Thus, slope of the multi-dip components in the original data can be robustly obtained from velocity-slope conversion using the velocity spectra of different dipping components. Field data example further confirms the validity of the proposed algorithm in the practical situation.

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