Geophysical Journal International

Geophys. J. Int. (2016) **204,** 768–779 doi: 10.1093/gji/ggv484
GJI Seismology

Velocity analysis of simultaneous-source data using high-resolution semblance—coping with the strong noise

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Accepted 2015 November 4. Received 2015 November 3; in original form 2015 September 14

SUMMARY

Direct imaging of simultaneous-source (or blended) data, without the need of deblending, requires a precise subsurface velocity model. In this paper, we focus on the velocity analysis of simultaneous-source data using the normal moveout-based velocity picking approach.We demonstrate that it is possible to obtain a precise velocity model directly from the blended data in the common-midpoint domain. The similarity-weighted semblance can help us obtain much better velocity spectrum with higher resolution and higher reliability compared with the traditional semblance. The similarity-weighted semblance enforces an inherent noise attenuation solely in the semblance calculation stage, thus it is not sensitive to the intense interference. We use both simulated synthetic and field data examples to demonstrate the performance of the similarity-weighted semblance in obtaining reliable subsurface velocity model for direct migration of simultaneous-source data. The migrated image of blended field data using prestack Kirchhoff time migration approach based on the picked velocity from the similarity-weighted semblance is very close to the migrated image of unblended data.

Key words: Image processing; Controlled source seismology.

INTRODUCTION

Simultaneous-source shooting is a breakthrough in modern seismic acquisition, which can tremendously increase the acquisition efficiency and improve the data quality (Beasley *et al.* 1998; Berkhout 2008; Abma & Yan 2009). In blended acquisition, more than one source is shot simultaneously, regardless of the interference. When more than one source is involved in acquisition, either a denser or a wider shot coverage can be obtained for a given constant acquisition period. The ‘wider’ coverage (Fig. 1b) here refers to a higher acquisition efficiency while the ‘denser’ coverage (Fig. 1a) refers to a better-sampled seismic data set. The attractive benefits are compromised by the challenges in dealing with strong interference from simultaneous sources in the acquired seismic data. We can either separate the blended sources into individual ones as if they were acquired independently, which is also called deblending (Chen 2014; Gan *et al.* 2016), or directly migrate the blended data using newly developed imaging schemes (Tang & Biondi 2009; Verschuur & Berkhout 2011). Deblending can provide similar data as the conventional acquisition and thus not require a change in post-processing and imaging algorithms, but need specific computationally expensive technique for the pre-processing (Abma & Yan 2009; Abma 2014). Direct imaging does not require any pre-processing steps for observed data and thus enjoys the benefit of high efficiency, but calls for a tremendously different processing workflow (Xue *et al.* 2014; Chen *et al.* 2015c).

Because of many reported success of deblending, more and more focus is now moved towards the direct imaging of blended data. However, one of the most important components in the direct imaging of simultaneous-source data is the macro subsurface velocity model of the targeted area. In this paper, we focus on the velocity analysis of the simultaneous-source data. We demonstrate that it is possible to directly apply the common velocity scanning procedures to the blended data in the common-midpoint (CMP) domain. We also propose to use the newly developed similarity-weighted semblance (Chen *et al.* 2015b; Gan *et al.* 2015a) to perform the velocity analysis. Both synthetic and field data examples show that the similarity-weighted semblance can help obtain higher-resolution and more reliable velocity spectrum than the conventional semblance, especially in the case of simultaneous-source data. The direct imaging of simultaneous-source data based on the directly picked velocity is also carried out via the prestack Kirchhoff time migration (PSKTM) approach. The performance shows that the migrated image from blended data based on the picked velocity from similarity-weighted semblance is very close to the migrated image from unblended data.

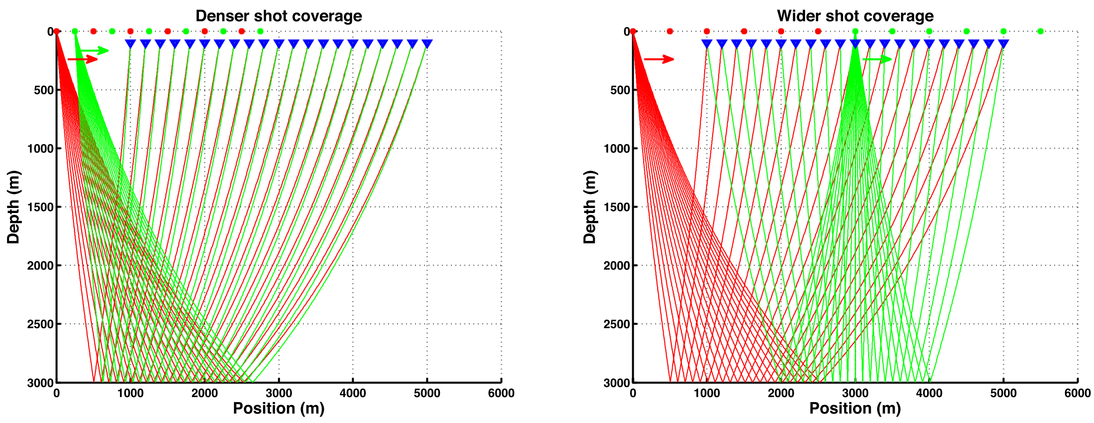


Figure 1. Demonstration of the simultaneous-source geometry. (a) Two-source shooting for denser coverage. (b) Two-source shooting for wider coverage. Red points denote shot positions for source 1. Green points denote shot positions for source 2. Blue points denote receiver positions. Red and green strings denote the shooting rays. Arrows denote the shooting directions. Borrowed from Chen *et al.* (2014b).

METHOD

Blended acquisition and direct imaging

For a constant-receiver survey, the simultaneous-source data can be expressed as

$$\mathbf{d} = \Gamma\mathbf{m}, \tag{1}$$

where $\mathbf{d}$ is the blended data, Γ is the blending operator, and $\mathbf{m}$ is the unblended data. The formulation of Γ has been introduced in Mahdad (2012) in detail. When considered in time domain, the Γ corresponds to blending different shot records onto one receiver record (node) according to the shot schedules of different shots. The Born modelling from seismic reflectivity to the primary reflections can be expressed as

$$\mathbf{m} = \mathbf{Lr}, \tag{2}$$

where $\mathbf{r}$ denotes the subsurface reflectivity model and $\mathbf{L}$ denotes the Born modelling operator. One way to remove the effects caused by the blending operator Γ is first solving eq. (1) and then solving eq. (2), which is referred to as 'deblending'. The general deblending framework can be summarized as (Chen *et al.* 2014a, 2015a)

$$\mathbf{m}_{n+1} = \mathbf{S}(\mathbf{m}_n + \lambda\Gamma^*(\mathbf{d} - \Gamma\mathbf{m}_n)), \tag{3}$$

where $\mathbf{S}$ is called the shaping operator, which is used to constrain the current model, and λ is the step size of the updated misfit. Γ^* denotes the adjoint of Γ. $\mathbf{m}_n$ denotes the deblended data after nth iteration.

Another way for dealing with the simultaneous-source data is to solve the following equation for $\mathbf{r}$ directly, which is known as direct imaging of blended data,

$$\mathbf{d} = \mathbf{Fr}, \tag{4}$$

where $\mathbf{F} = \Gamma\mathbf{L}$.

Eq. (4) can be best solved using a least-squares (LS) based migration approach. More robust LS solvers involve adding constraints of structural coherency when inverting $\mathbf{r}$, either in a pre-conditioned LS formulation (Dai & Schuster 2011; Chen *et al.* 2015c) or in a shaping-regularized LS iterative framework (Fomel 2007b; Xue *et al.* 2014).

Because of the great success of deblending reported in the literature (Abma *et al.* 2010; Mahdad *et al.* 2011; Beasley *et al.* 2012; Li *et al.* 2013; Chen 2015; Gan *et al.* 2015b; Zu *et al.* 2015) in the recent years, more and more focus is currently moving towards the direct imaging of blended data, which can be more efficient and can illuminate the surface better (Verschuur & Berkhout 2011; Berkhout *et al.* 2012). It is worth mentioning that the deblending step for the massive blended data requires large computational resources (mainly for the parallel processing of a huge number of common receiver gathers) and a long processing period because of the thousands of iterations used for each common receiver gather. If the direct imaging can obtain a good result, we can obtain a big saving in both computational resources and processing period. However, a key aspect for the success of direct imaging is the macro velocity model of subsurface. Either tomography based velocity analysis or Born-approximation wave-equation based velocity inversion, requires an initial acceptable velocity model from the very noisy blended data (Fig. 9a shows an example). In the next section, we will introduce a way for obtaining high-resolution and high-fidelity velocity spectrum from blended data, using the recently developed similarity-weighted semblance.

Velocity analysis of blended data using similarity-weighted semblance

The conventional semblance is defined by Neidell & Taner (1971) as

$$C[i] = \frac{\sum_{j=i-M}^{i+M}\left(\sum_{k=0}^{N-1} s[j,k]\right)^2}{N\sum_{j=i-M}^{i+M}\sum_{k=0}^{N-1} s^2[j,k]}, \tag{5}$$

where i and j are time sample indices, $C[i]$ denotes the conventional semblance for time index i, $2M+1$ is the length of the smoothing window along the time axis, and $s[j,k]$ is the trace amplitude at time index j and trace number k of the normal moveout-corrected CMP gather.

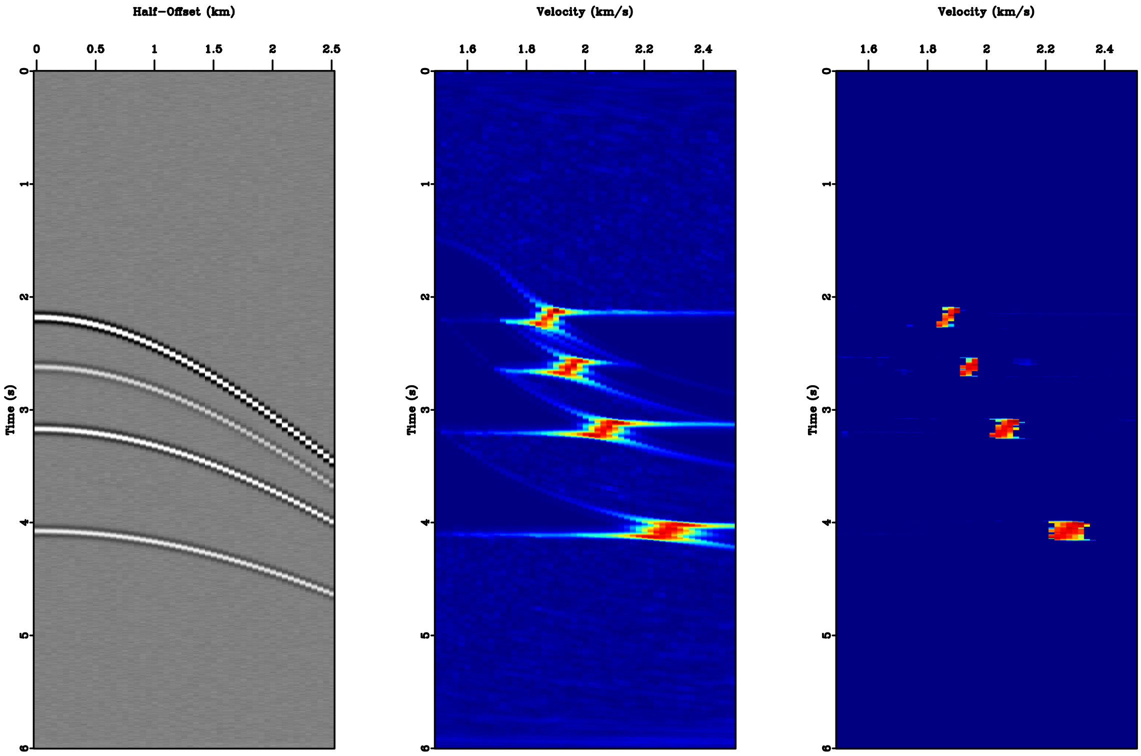


Figure 2. A brief comparison between the similarity-weighted semblance and the conventional semblance. Left: simple synthetic data. Middle: semblance map using the conventional semblance. Right: semblance map using the similarity-weighted semblance.

The weighted semblance introduced in Chen *et al.* (2015b) can be summarized as

$$W[i]=\frac{\sum_{j=i-M}^{i+M}\left(\sum_{k=0}^{N-1}s[j,k]w[j,k]\right)^2}{\sum_{j=i-M}^{i+M}\left(\sum_{k=0}^{N-1}s^2[j,k]\sum_{k=0}^{N-1}w^2[j,k]\right)}, \tag{6}$$

where $W[i]$ denotes the weighted semblance, $w[j, k]$ denotes the weighting function for time index j and trace number k.

There have existed several weighting criteria, such as the AB semblance (Fomel 2009), offset-prior semblance (Luo & Hale 2012), and the similarity-weighted semblance (Chen *et al.* 2015b). As the similarity-weighted semblance can improve the resolution of velocity spectrum greatly, and has the possibility to subtract noise effect, we choose the local similarity (Fomel 2007a) to weight different traces:

$$w[j,k]=\mathcal{L}(s[j,k],r[j]), \tag{7}$$

where $\mathcal{L}(\mathbf{x},\mathbf{y})$ denotes the local similarity between traces $\mathbf{x}$ and $\mathbf{y}$, $r[j]$ denotes the jth time point for a selected reference trace $\mathbf{r}$. In this paper, the reference trace is chosen as the stacked trace using a conventional stacking technique. Fig. 2 shows a demonstration of the velocity spectrum calculated using the similarity-weighted semblance compared with the velocity spectrum calculated using the traditional semblance. The left panel in Fig. 2 shows a simple synthetic data with four hyperbolic events. The middle and right panels show the velocity spectrum calculated using the traditional and the proposed semblance, respectively. It is obvious that the similarity-weighted semblance is of high resolution.

It is worth mentioning that, the selection of the reference trace needs several iterations in practice. It is obvious that the similarity-weighted semblance is calculated with an inherent denoising ability. The noise attenuation involved in the similarity-weighted semblance is much similar to that used in Liu *et al.* (2009) for attenuating random noise in the stacking process. Because of intense interference existing in the simultaneous-source data, conventional semblance will decrease the resolution because of the corruption by the blending interference. However, the beauty of the similarity-weighted semblance is that it enforces an inherent noise attenuation solely in the semblance calculation stage, without any extra process specifically designed for noise attenuation. The key element that enables the anti-noise ability of the similarity-weighted semblance is the local similarity based weights. In the next part, we will review the basic theory of the local similarity.

Local similarity

A common way to measure the similarity between two signals is to calculate the global correlation coefficient:

$$\gamma=\frac{\sum_{i=1}^{N}a(i)b(i)}{\sqrt{\sum_{i=1}^{N}a^2(i)\sum_{i=1}^{N}b^2(i)}}, \tag{8}$$

where γ is the global correlation coefficient, N denotes the number of samples of the signals $\mathbf{a}$ and $\mathbf{b}$. In order to calculate the similarity

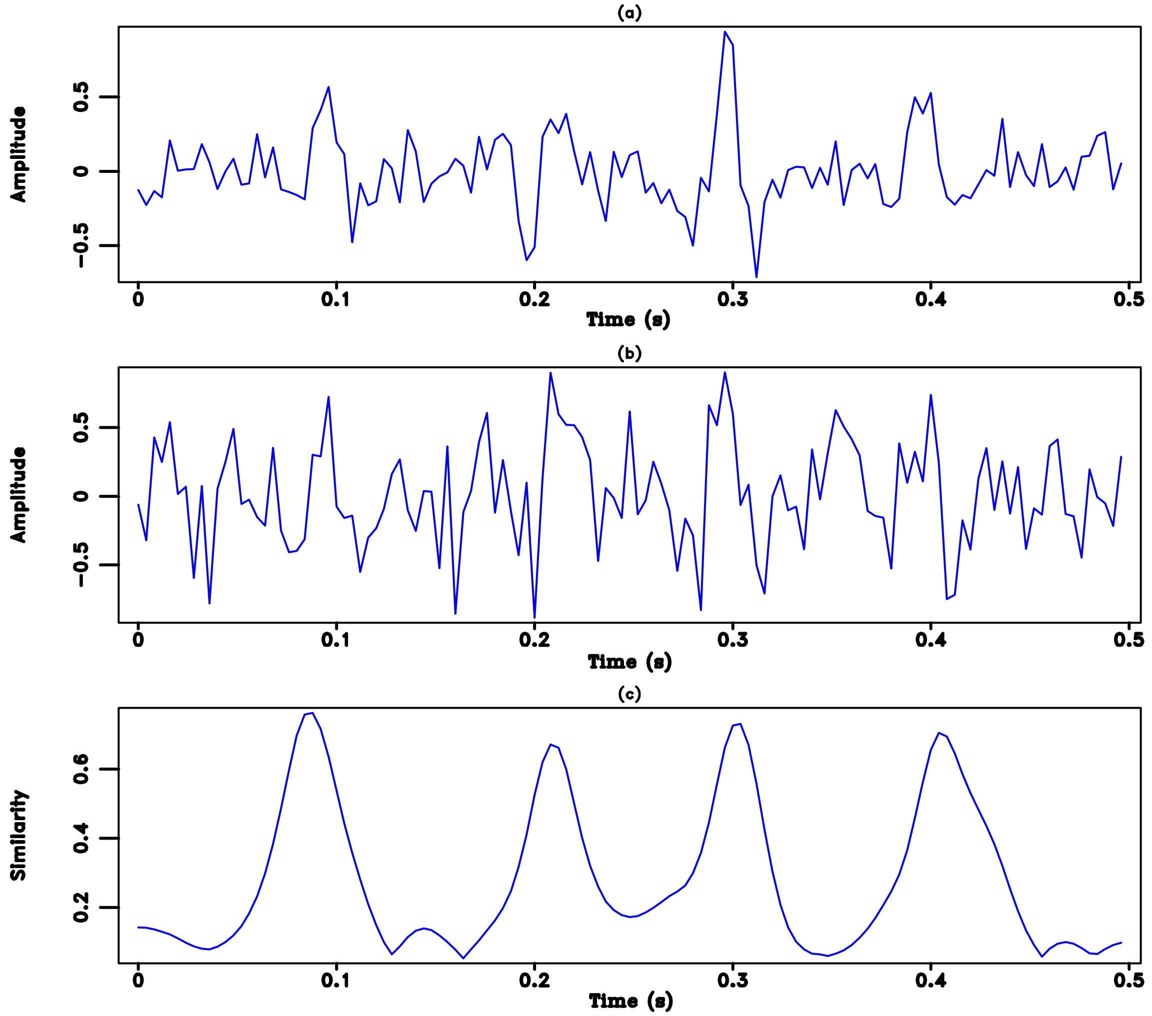


Figure 3. Local similarity for 1-D signal. (a,b) The same trace with different level of noise. (c) Calculated local similarity.

between two signals locally, one can use the localized correlation coefficient:

$$\gamma_m(t) = \frac{\sum_{i=t-m/2}^{t+m/2} a(i)b(i)}{\sqrt{\sum_{i=t-m/2}^{t+m/2} a^2(i) \sum_{i=t-m/2}^{t+m/2} b^2(i)}}, \quad (9)$$

where $\gamma_m(t)$ denotes the local correlation coefficient, m is the local window size.

Fomel (2007a) designed an elegant way to calculate the local similarity:

$$\gamma(t) = \sqrt{\gamma_1(t)\gamma_2(t)}, \quad (10)$$

$$\gamma_1(t) = \arg\min_{\gamma_1(t)} \left(\sum_t (a(t) - \gamma_1(t)b(t)) + R(\gamma_1(t)) \right), \quad (11)$$

$$\gamma_2(t) = \arg\min_{\gamma_2(t)} \left(\sum_t (b(t) - \gamma_2(t)a(t)) + R(\gamma_2(t)) \right). \quad (12)$$

Eq. (10) represents that the local similarity can be expressed as the product of two vectors that are the solutions of two minimization problems. R is a regularization operator for constraining γ_1 and γ_2. R can be chosen as a local triangular smoother to enforce the smoothness of vectors γ_1 and γ_2, and then eqs (11) and (12) can be solved using the shaping regularization (Fomel 2007b):

$$\gamma_1 = [\lambda_1^2\mathbf{I} + \mathcal{S}(\mathbf{B}^T\mathbf{B} - \lambda_1^2\mathbf{I})]^{-1}\mathcal{S}\mathbf{B}^T\mathbf{a}, \quad (13)$$

$$\gamma_2 = [\lambda_2^2\mathbf{I} + \mathcal{S}(\mathbf{A}^T\mathbf{A} - \lambda_2^2\mathbf{I})]^{-1}\mathcal{S}\mathbf{A}^T\mathbf{b}, \quad (14)$$

where $\mathbf{A}$ is a diagonal operator composed from the elements of $\mathbf{a}$: $\mathbf{A} = \mathrm{diag}(\mathbf{a})$ and $\mathbf{B}$ is a diagonal operator composed from the elements of $\mathbf{b}$: $\mathbf{B} = \mathrm{diag}(\mathbf{b})$. $\mathcal{S}$ is a smoothing operator, and λ_1 and λ_2 are two parameters controlling the physical dimensionality and enabling fast convergence when inversion is implemented iteratively. These two parameters can be chosen as the LS norms of $\mathbf{A}$ and $\mathbf{B}$ (Fomel 2007a).

The local similarity algorithm can be used for the calculation of signals of any dimension. For 1-D signals, the meanings of eqs (13) and (14) are intuitive. For 2-D or higher-dimensional signals, each signal is first reshaped into a 1-D signal and then follows eqs (13) and (14) to calculate the local similarity vector. The smoothing operator is applied to the 2-D or multi-dimensional form of the original signal to enforce the smoothness in any dimension. Figs 3

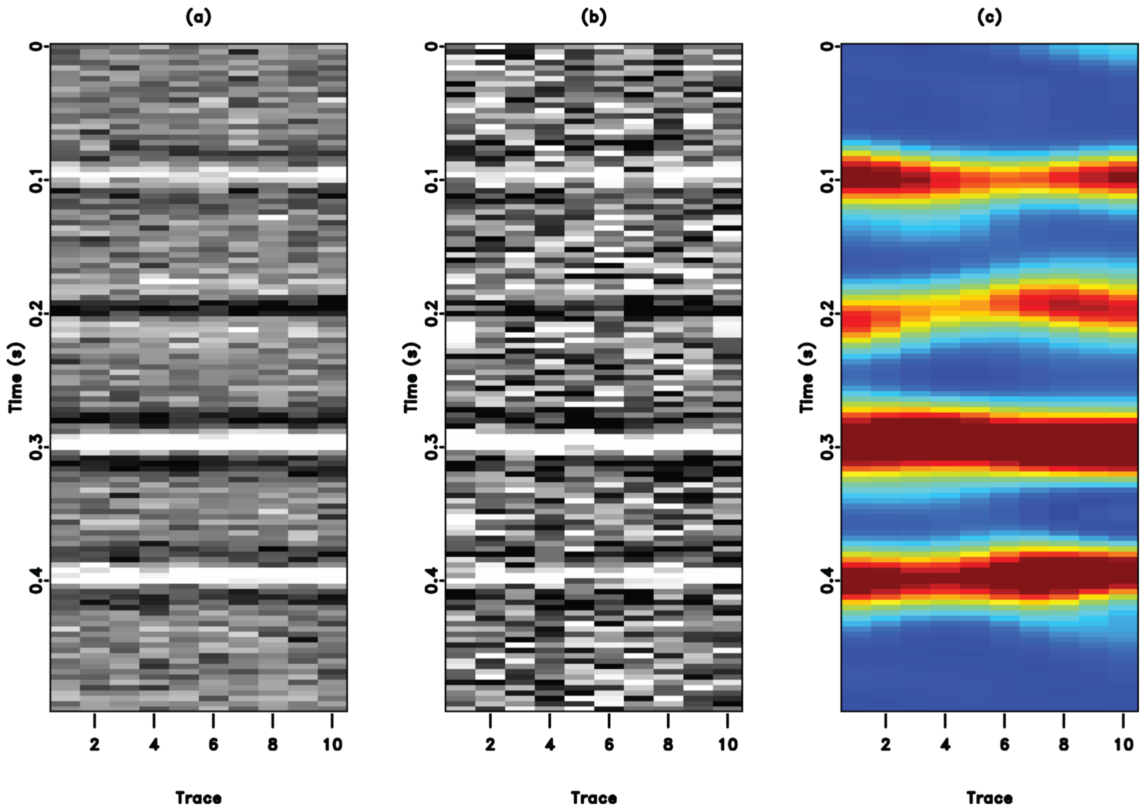


Figure 4. Local similarity for 2-D signal. (a,b) The same flattened gather with different level of noise. (c) Calculated local similarity.

and 4 show demonstrations for both 1-D and 2-D signals. Figs 3(a) and (b) show the same trace with different level of noise. Fig. 3(c) shows the calculated local similarity for the 1-D signal. Figs 4(a) and (b) show the same flattened gather with different level of noise. Fig. 4(c) shows the calculated local similarity for the 2-D signal. From the two examples, we can conclude that the local similarity can effectively obtain smooth and reasonable measurements for both 1-D and 2-D signals. The peaks in the calculated local similarity indicate the position of useful wavelets correctly.

EXAMPLES

The first example is a synthetic example. Fig. 5 shows the unblended and blended data in the CMP domain. The blending fold is very high and thus the blended data is very noisy. It should be mentioned that before the processing, we need to apply the domain transformation, which transforms the data from shot domain to midpoint domain. The domain transformation corresponds to the following transformation relation:

$$\mathbf{m} = \frac{1}{2}(\mathbf{s}+\mathbf{r}),$$

$$\mathbf{h} = \frac{1}{2}(\mathbf{s}-\mathbf{r}), \tag{15}$$

where $\mathbf{m}$ and $\mathbf{h}$ denote the midpoint and offset locations, $\mathbf{s}$ and $\mathbf{r}$ denote the source and receiver locations. Here, we leave out the domain transformation (Chen *et al.* 2014b) between common shot point (CSP) domain and CMP domain, and just show the data in the CMP domain. Fig. 6 shows the comparison of the velocity spectrum using conventional semblance and similarity-weighted semblance. As we know the exact velocity of this synthetic example, we can compare the velocity spectrum with the true velocity in order to judge the performance of different semblance approaches. As we can see from the comparison, the similarity-weighted semblance can obtain obviously higher resolution and more reliable spectrum. The black strings on the top of the spectrum maps denote the true velocity. The two frame boxes highlight two regions of obvious difference. From the two highlighted frame boxes, it is much clearer that the similarity-weighted semblance can get more reliable result.

The second example is a field data example with multiples. Fig. 7 shows the unblended and blended data in the CMP domain. Fig. 8 shows a comparison between different velocity spectrum for both unblended and blended data. Because in this case, we do not have the true velocity model, we can only use the spectrum of unblended data as a reference. The left and middle left figures in Fig. 8 correspond to the velocity spectrum of unblended data using conventional semblance and similarity-weighted semblance, respectively. The middle right and right figures in Fig. 8 correspond to the velocity spectrum of blended data using conventional semblance and similarity-weighted semblance, respectively. In this case, we also have the spectrum of multiples. It is obvious that the similarity-weighted semblance can obtain higher resolution for both unblended and blended data. Comparing the middle right and right figures, we can conclude that the similarity-weighted semblance can be more reliable for velocity picking.

The third example is a numerically blended field data example in the case of high blending ratio (the interference is very strong). The numerically blended data is shown in Fig. 9(a). Because of the strong

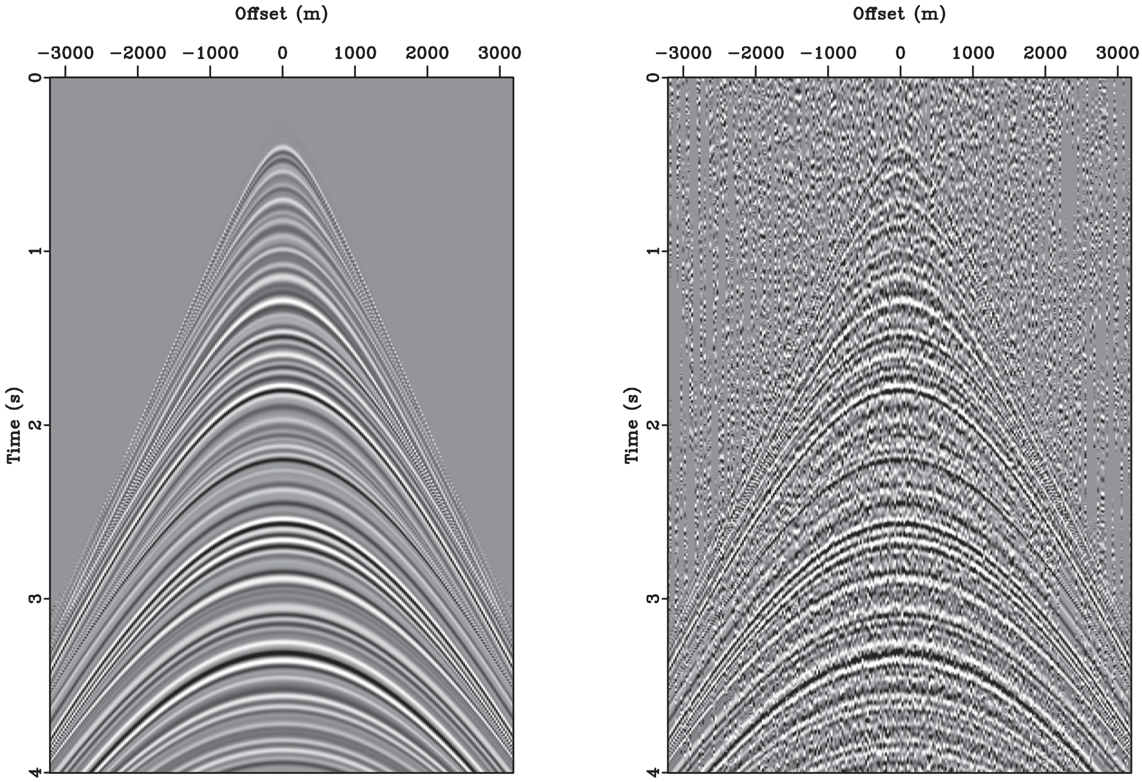


Figure 5. Synthetic data example. Left: unblended CMP gather. Right: blended CMP gather.

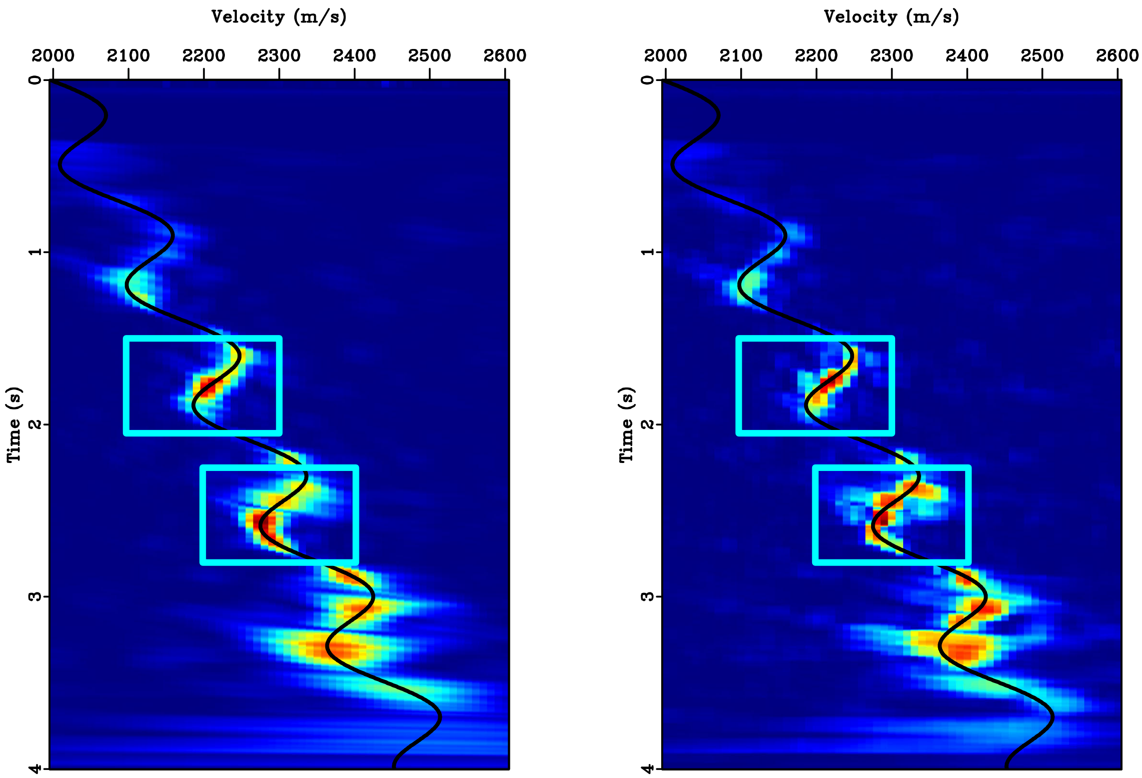


Figure 6. Left: velocity spectrum of blended data using the conventional semblance. Right: velocity spectrum of blended data using the high-resolution semblance.

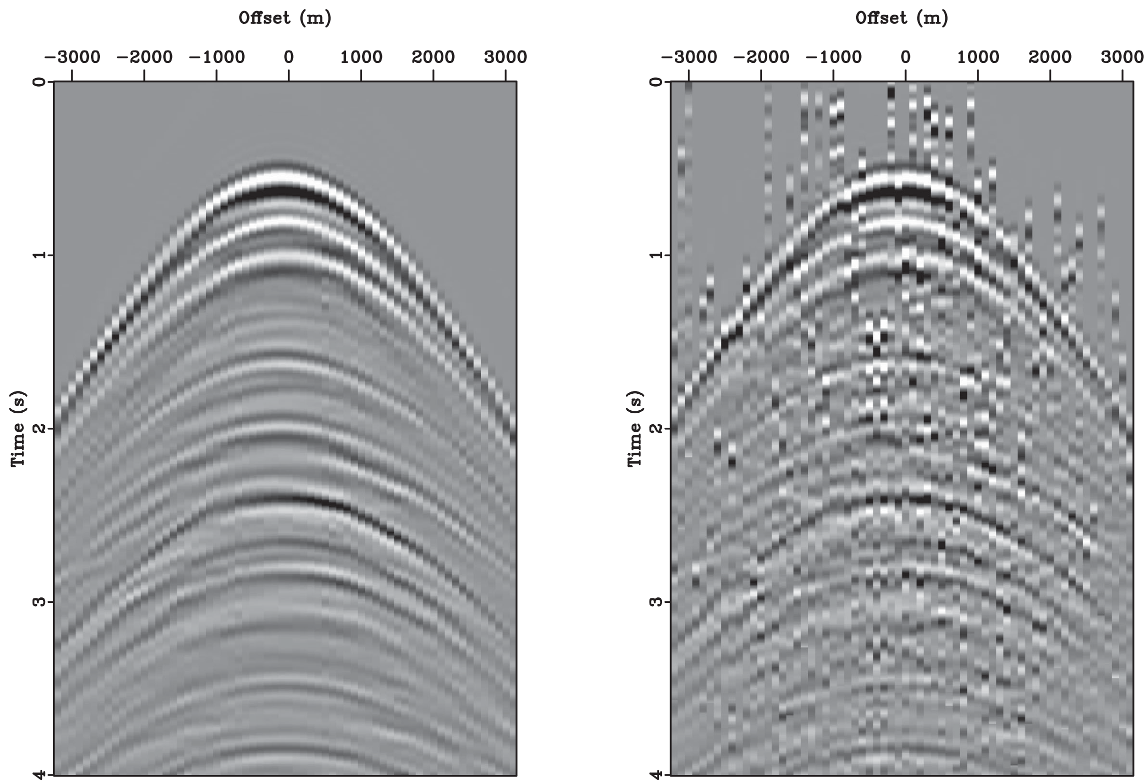


Figure 7. Field data example. Left: unblended CMP gather. Right: blended CMP gather.

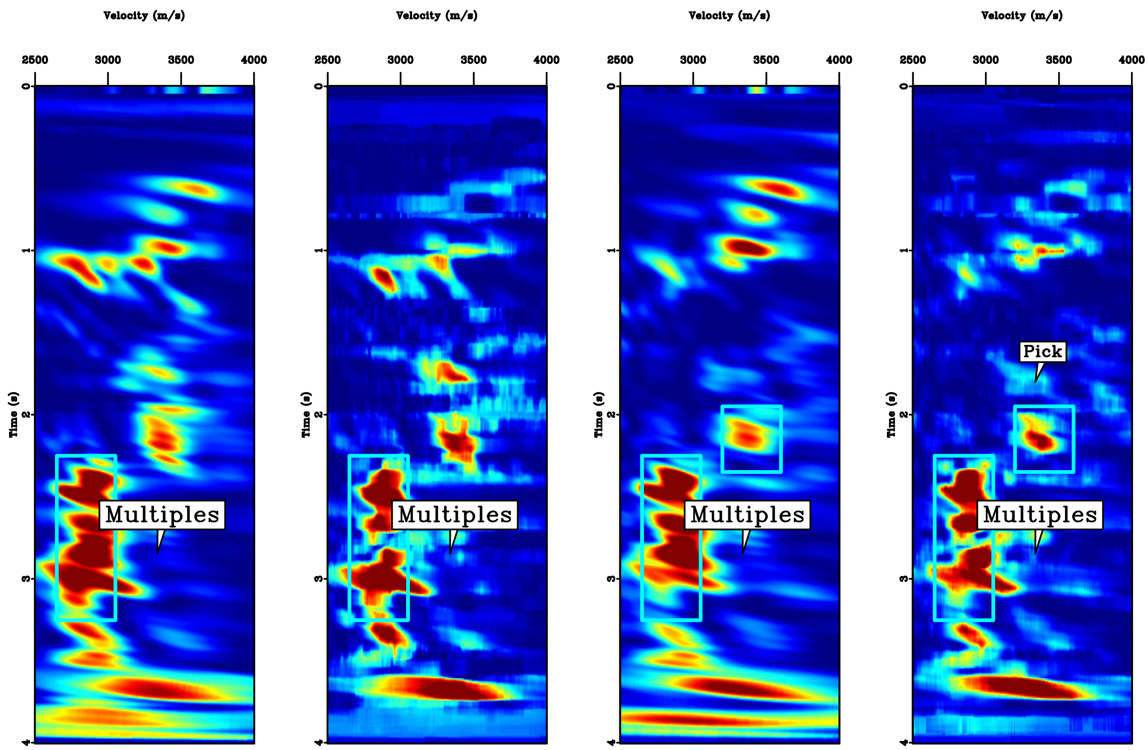


Figure 8. Left: velocity spectrum of unblended data using conventional semblance. Middle left: velocity spectrum of unblended data using the high-resolution semblance. Middle right: velocity spectrum of blended data using the conventional semblance. Right: velocity spectrum of blended data using the high-resolution semblance.

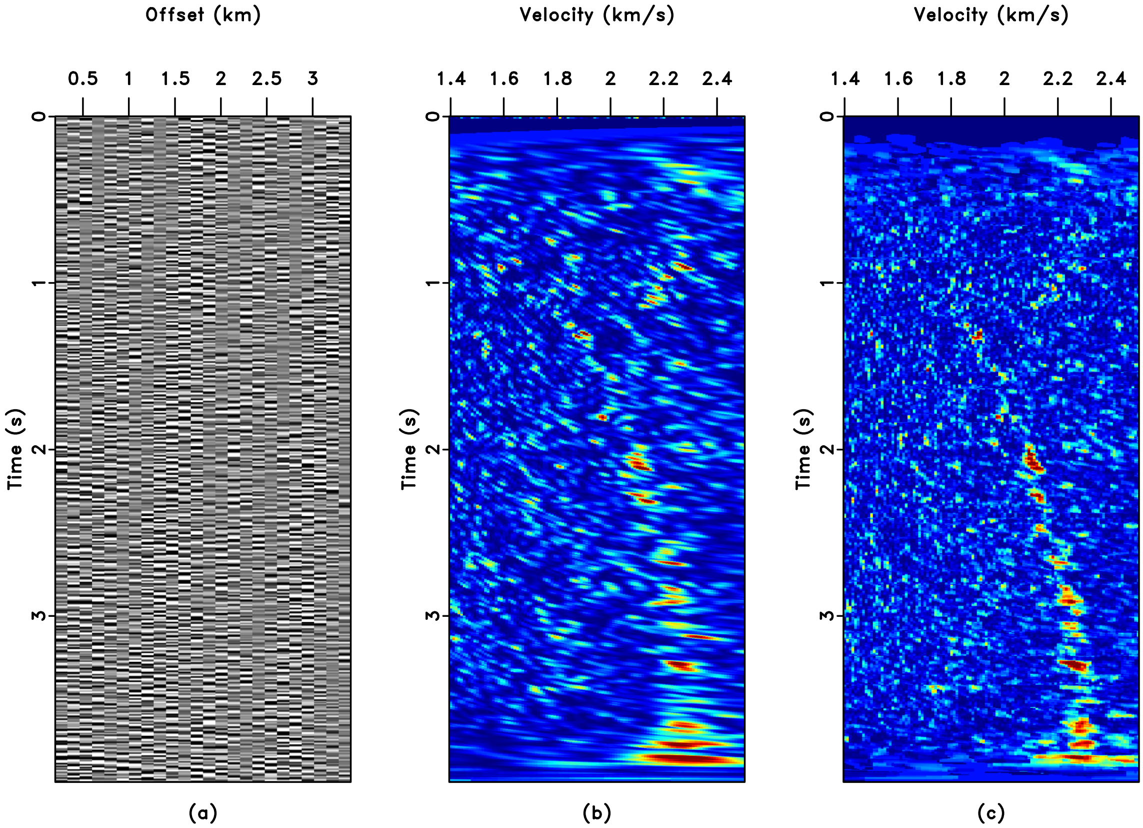


Figure 9. (a) Blended CMP gather with strong blending interference. (b) Velocity spectrum using the conventional semblance. (c) Velocity spectrum using the high-resolution semblance.

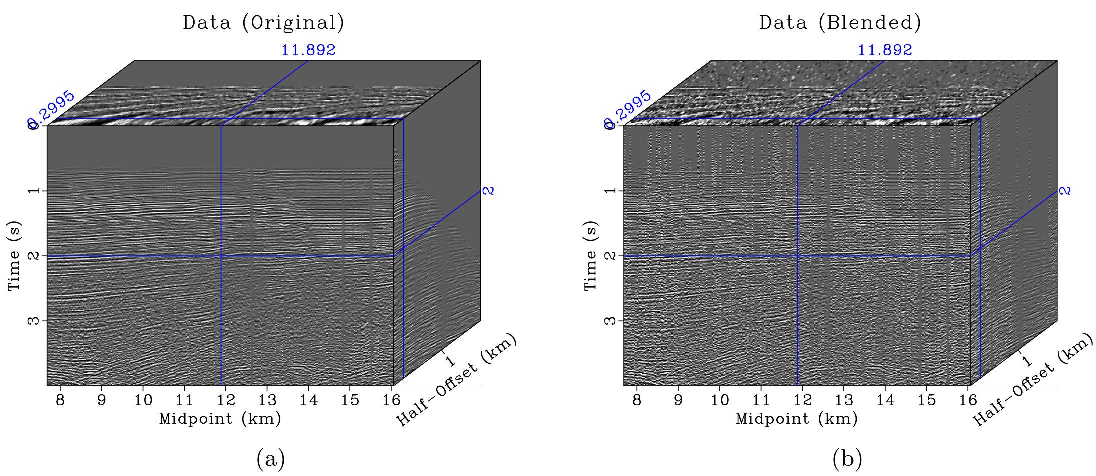


Figure 10. Gulf of Mexico data example. (a) Unblended field data. (b) Numerically simulated field data.

blended interference, it is hard to detect the useful reflections. In this example, the conventional semblance cannot obtain an acceptable velocity spectrum, as shown in Fig. 9(b). The peaks in the velocity spectrum map are nearly smeared in the background noise. However, we can still obtain well-behaved velocity peaks, using the proposed high-resolution similarity-weighted semblance, which distinguish themselves with the background noise. The peaks can be picked either manually or automatically.

The fourth example is a numerically blended pre-stack field data. Figs 10(a) and (b) show the unblended and blended data that have been sorted from CSP gathers to CMP gathers. This example is used to simulate the independent marine-streamer simultaneous shooting

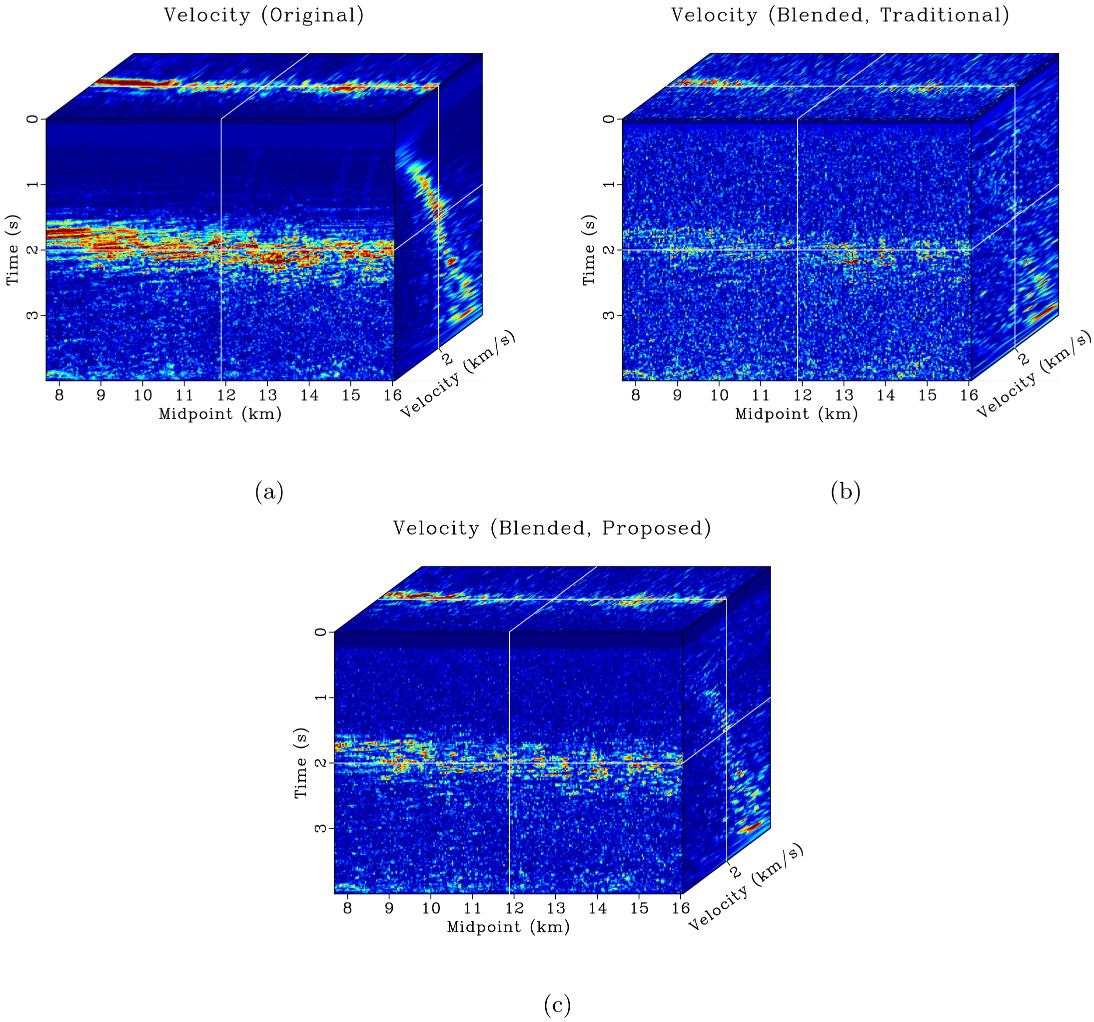


Figure 11. Comparison of velocity spectrum. (a) Velocity analysis of unblended data using the traditional approach. (b) Velocity analysis of blended data using the traditional approach. (c) Velocity analysis of blended data using the proposed approach.

(IMSSS) acquisition (Chen *et al.* 2014b). The blending interference is so strong that the useful reflections are nearly smeared in the noise. Fig. 11(a) shows the velocity spectrum of the unblended data using the traditional semblance. Fig. 11(b) shows the velocity spectrum of the blended data using the traditional semblance. Fig. 11(c) shows the velocity spectrum of the blended data using the proposed high-resolution semblance. It is obvious that the traditional semblance can obtain good performance for clean unblended data. However, the traditional semblance cannot obtain a reasonable velocity spectrum for the blended data. Because of the strong blending interference, the traditional semblance cannot generate energy peaks in the spectrum that can be easily picked. Fortunately, the high-resolution similarity-weighted semblance can help obtain much focused peaks in the velocity spectrum that can be picked. With the automatically picked velocity (Fomel 2009) from the velocity spectrum shown in Fig. 11, we can obtain their corresponding migration results. Here, it is worth giving a brief introduction about the automatic velocity picking algorithm. Although the automatic velocity picking problem was mentioned by several researchers in the literature (Adler & Brandwood 1999; Sarkar & Baumel 2000; Harlan 2001; Arnaud *et al.* 2004), we use the approach proposed in Fomel (2009). The main principle of the approach is to solve the following eikonal equation

$$\left(\frac{\partial T}{\partial v}\right)^2 + \frac{1}{\alpha^2}\left(\frac{\partial T}{\partial t}\right)^2 = \mathrm{e}^{-2w(t,v)}, \tag{16}$$

where T is the traveltime, $w(t, v)$ corresponds to the semblance spectrum, and α denotes a scaling parameter. After obtaining a finite-difference solution of eq. (16), we can extract the picking trajectory $v(t)$ by tracking backward along the traveltime gradient direction.

The migrated profiles using the PSKTM algorithm for different cases are shown in Fig. 12. Fig. 12(a) shows the migrated profile for unblended data using the traditional semblance method. Figs 12(b) and (c) show the migrated profiles for blended data using the traditional semblance and the proposed high-resolution semblance, respectively. In this example, we can consider Fig. 12(a) as the true answer, and judge the performance of different approaches by comparing the migrated results with Fig. 12(a). We can observe huge difference between Figs 12(a) and (b). However, Figs 12(a) and (c) are more similar. We can confirm this observation by zooming a part from the original migrated

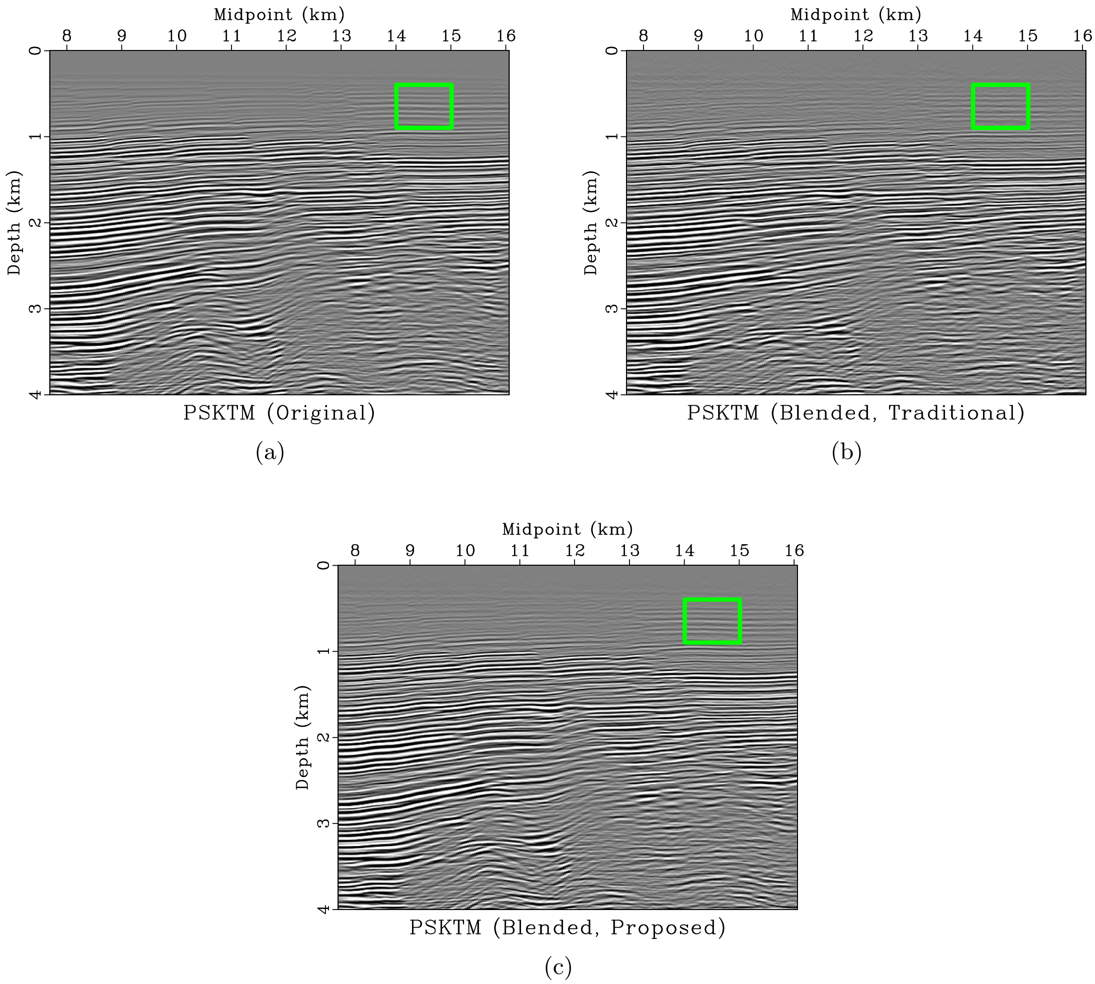


Figure 12. Comparison of migration results. (a) PSKTM of unblended data using the traditional picked velocities. (b) PSKTM of blended data using the traditional approach. (c) PSKTM of blended data using the proposed approach.

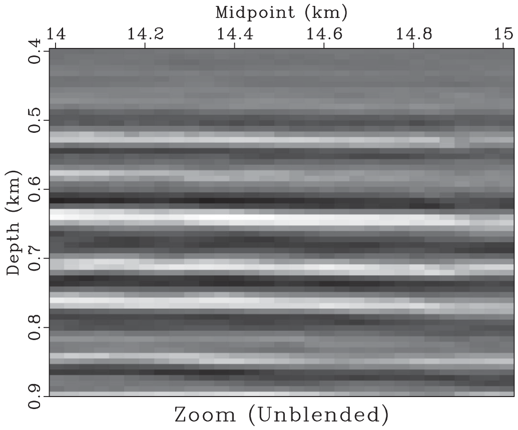
profiles. Fig. 13 shows the zoomed sections that correspond to the frame boxes shown in Fig. 12. It is more obvious that Figs 13(a) and (c) show very similar reflections, while Fig. 13(b) is much different from the other two cases. The erroneous reflections in Fig. 13(b) indicate erroneous picked velocities using the traditional semblance.

CONCLUSION

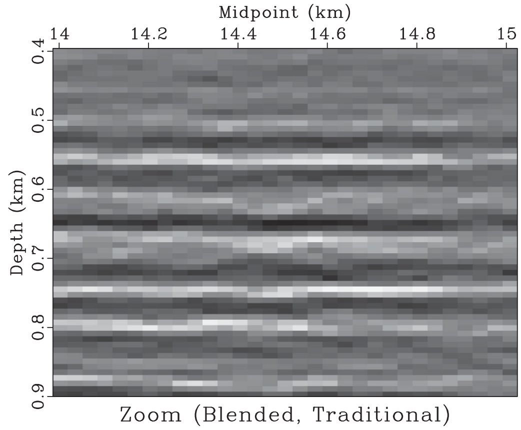
We have demonstrated that it is possible to use normal moveout-based velocity analysis approach to obtain an acceptable velocity model from the very noisy simultaneous-source data. The similarity-weighted semblance can obtain a better velocity spectrum than the conventional semblance, with higher resolution and reliability. When the blending interference is so strong that the seismic reflections cannot be observed, the similarity-weighted semblance can still show plausible energy peaks in the velocity spectrum, and the peaks can be picked easily. We use both simulated synthetic and field data examples to show the potential of the similarity-weighted semblance in velocity analysis of simultaneous-source data. We also compare the migrated images of unblended field data and numerically blended field data using different picked velocities. The migrated image of blended data using the picked velocity from the similarity-weighted semblance is very close to the migrated image of unblended data, which shows great potential that the separation of simultaneous sources is no longer necessary.

ACKNOWLEDGEMENTS

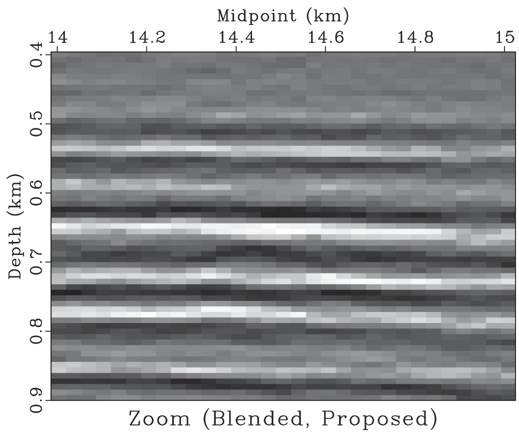
We would like to thank Pan Deng and Keling Chen for helpful discussions about similarity-weighted semblance, Jiang Yuan, Zhaoyu Jin, Ray Abma, Min Zhou, Araz Mahdad and Sergey Fomel for inspiring discussions about simultaneous-source acquisition. We also thank Ingo Grevemeyer, and two anonymous reviewers for constructive suggestions that improve the original manuscript greatly. This work is partially supported by the National Natural Science Foundation of China (Grant No. 41274137), the National Science and Technology of Major Projects of China (Grant No. 2011ZX05019-006), the National Engineering Laboratory of Offshore Oil Exploration, and the Texas Consortium for Computational Seismology (TCCS).



(a)



(b)



(c)

Figure 13. Comparison of zoomed migration results. (a) PSKTM of unblended data using the traditional approach. (b) PSKTM of blended data using the traditional approach. (c) PSKTM of blended data using the proposed approach.

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