MULTIPLE SUBTRACTION USING A HYBRID LEAST-SQUARES FILTERING, NON-LINEAR WEIGHTING AND COMPLEX CURVELET DOMAIN APPROACH

LIEQIAN DONG[1,2], MUGANG ZHANG [1], DEYING WANG [2], YIMENG ZHANG[1], CHANGHUI WANG[1], ZHONG JIANG [1]

[1] *BGP, CNPC, Zhuozhou 072751, P.R. China. donglieqian@bgpintl.com*
[2] *Key laboratory of Depositional Mineralization & Sedimentary Mineral of Shandong Province, Shandong University of Science and Technology, Qingdao 266590, P.R. China.*

(Received April 4, 2017; revised version accepted July 20, 2018)

ABSTRACT

Dong, L., Zhang, M., Wang, D., Zhang, Y., Wang, C. and Jiang, Z., 2018. Multiple subtraction using a hybrid least-squares filtering, non-linear weighting and complex curvelet domain approach. *Journal of Seismic Exploration*, 27: 433-444.

The study of de-multiple methods is a very important task in seismic data processing. For the typical prediction-subtraction methods, predicted multiples usually are never perfect and need adaption. However, considering the absence of orthogonality between predicted multiples and the primaries in the data, standard matching or subtraction methods often do not provide satisfactory results. To resolve this issue, primary/multiple separation via the curvelet domain has been introduced. However, the threshold methods based on the real curvelet transform (RCT) are sensitive to event positioning errors. In case of a slight event mispositioning, the amplitude of the RCT's coefficients change dramatically. For that reason, a primary and multiple separation scheme based on least-squares (LS) matching and complex curvelet transform (CCT) is introduced in this paper. Firstly, the LS matching method is applied to do a rough amplitude matching and global time shift correction, then an optimal problem can be built and solved to correct the residual misfit in the CCT domain by taking advantage of the amplitude shift invariance property of the CCT. In addition, a non-linear primary protection masking process preserves most primaries during the process. Validation of this hybrid procedure on synthetic and field data shows that the primaries can be correctly recovered from the original data.

KEY WORDS: de-multiple, prediction-subtraction, least-squares, shift invariance, complex curvelet transform, non-linear masking.

0963-0651/18/$5.00

INTRODUCTION

In the seismic industry, the enhancement of the seismic imaging accuracy is an utmost goal for exploration geophysicists. However, in most cases, the existence of multiples seriously degrades the signal to noise ratio of seismic data, and causes difficulties for effective signal identification. Therefore, to effectively suppressing multiples is always a key task in seismic exploration.

In view of the differences of the dynamic features between the predicted multiple model and the actual one (Verschuur et al., 1992), a matching or correction method is usually adopted to separate primaries from multiples. Presently, conventional matching or separating methods mainly involve L2-based methods (Verschuur and Berkhout, 1997; Wang, 2003; Guitton, 2003; Dong et al., 2013), independent component analysis-based methods (Lu, 2006), regularized nonstationary regression-based methods (Fomel, 2009), curvelet domain threshold subtraction methods (Herrmann et al., 2007 and 2008; Rayan et al., 2007). Each method can obtain a desirable de-multiple result under some given conditions. However, the above methods may fail when the non-orthogonality or the mis-positioning problems can not be effectively resolved. Therefore, a primary and multiple separation approach based on LS matching and the CCT is introduced in this paper. Firstly, the LS matching method is applied to correct the bulk amplitude and time shift errors (Herrmann et al., 2007). Then, an optimal problem is built and solved to correct the residual misfit in the CCT domain through using the amplitude shift invariance property of the CCT. In addition, for the purpose of protecting the primary events, a non-linear masking filter is applied in advance, which can preserve most of primary signals. Next, the residual primary data can be recovered using the proposed approach in the paper.

Construction and properties of the CCT

The construction of the CCT is similar to that of the RCT (Candès and Donoho, 2004). We can obtain the RCT coefficients of a signal first, and then construct real and imaginary parts of the CCT using two RCT coefficients with identical dip, position, frequency, but different phases with 90 degrees shift (Neelamani et al., 2010).

The construction of the CCT has the following features:

- The CCT has properties that can be used for signal-noise separation similar to the RCT. For example, random noise removal (Kumar et al., 2009) and coherent noise suppression (Neelamani et al., 2008).

- The special construction of the CCT overcomes the deficiency of shift variance of the RCT. To be precise, the CCT coefficients almost remain unchanged while the RCT coefficients change dramatically even if seismic event has a slight shift in time. Fig 1 shows the contrast of the coefficient changes of the RCT and the CCT. Fig 1a shows a flattened event (left) where the second event has a three points downward shift (right). Fig 1b denotes the RCT coefficients of Fig 1a respectively. From the corresponding color differences, we can see that the coefficients change dramatically at the same position. On the other hand, the corresponding CCT coefficients remain almost unchanged as shown in Fig 1c.

- The real and imaginary parts of the CCT have 90 degrees difference in phase. Like the Fourier transform, the event can be shifted by changing the phase of the CCT coefficients that represent the event. Note that the 90 degrees phase-shift relationship between the CCT's real and imaginary parts is similar to the relationship between the Fourier basis functions. If the event shifts in time by Δt, the phase will change by $\omega\Delta t$ while the magnitude remains unchanged. For similar reasons, if the phase of the CCT's coefficients changes by $\omega\Delta t$, the event will also have a shift in time by Δt, as shown in Fig 2.

MULTIPLE SUBTRACTION METHOD AND FLOW

The LS matching method is one of the commonly used methods to solve an inverse problem, where it assumes that for an optimum subtraction the residual errors take a minimum,

$$\arg\min \| d - Fm \|_2^2 \quad , \tag{1}$$

where d and m are vectors containing the original dataset and the multiple model, respectively, and F denotes an amplitude matching operator.

Due to the non-orthogonality of seismic events, there will be some residual misfit left between multiple model and the actual multiple after the LS matching method. The curvelet transform has the excellent features to sparsely represent seismic events and it can map the primaries and multiples into different sets of curvelet coefficients in terms of different frequency, dip and location. Therefore, the primary and multiple separation method based on the curvelet transform is proposed by Herrmann et al. (2007). Unfortunately, the conventional RCT-based adaptive subtraction approach suffers from the inherent weakness of amplitude shift variance even though a slight time shift exists. For that reason, better results are obtained using the CCT instead of the RCT.

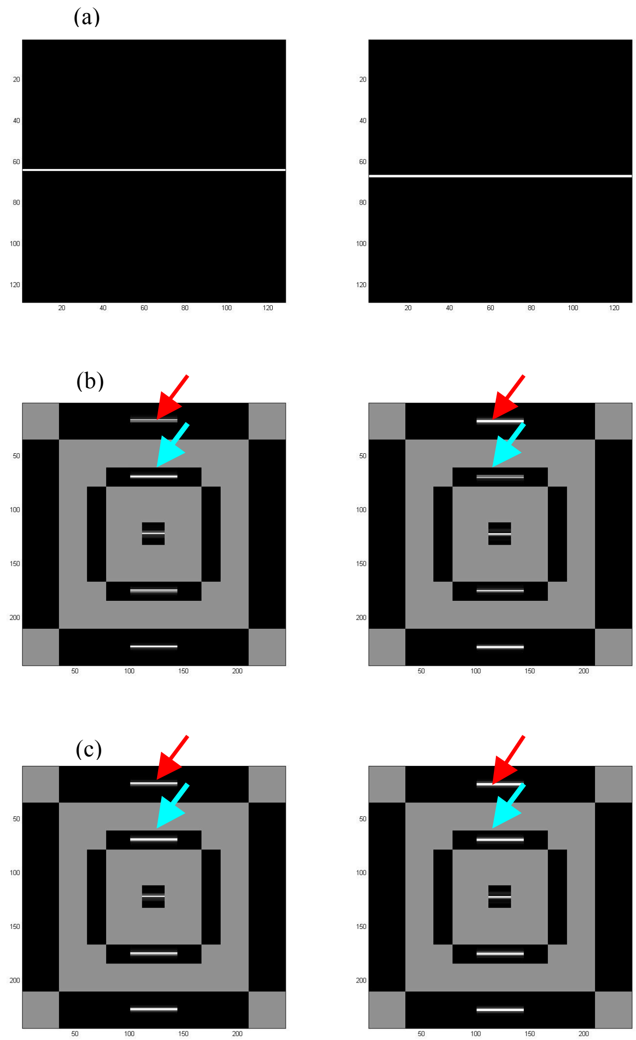

Fig. 1. Time shift sensitivity contrast of the RCT and the CCT. (a) 2D synthetic data with one event; (b) RCT coefficient representations of the corresponding data from Fig. (a); (c) CCT coefficient representations of the corresponding data from Fig. (a).

Based on the different frequency, dip and location between primaries and multiples, where the curvelet coefficients can be regarded as the weights, we build the following optimization problem in each sub-CCT domain:

$$\arg\min_{1\le k\le N} \| c_d^k - F^k c_{fm}^k \|_2^2 \quad . \tag{2}$$

In eq. (2), c_d^k represents CCT coefficients of the original data at the k-th scale. c_{fm}^k denotes CCT coefficients of the multiple model after the LS matching at the scale of k-th. N is the maximum CCT decomposition scales. F^k denotes a shaping filter at the k-th scale.

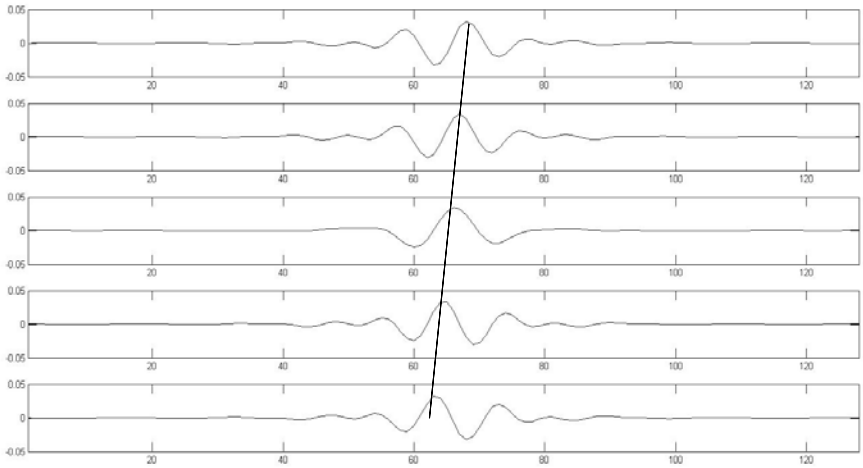

Fig. 2. Effect of changing a CCT coefficient's phase on the cross section of the seismic reflection piece that it represents.

To solve the above optimization problem, a threshold-based approach is adopted in each sub-CCT domain. The final recovered primary p is expressed as follows:

$$p = real\ (C^T \sum_{1\le k\le N} (T_\lambda(c_d^k,\ \ c_{fm}^k))) \quad , \tag{3}$$

where, C^T represents the inverse of CCT, $T_\lambda(\,,\,)$ is a threshold function which can be chosen as hard threshold function, soft threshold function or some modified threshold functions (Donoho, 1995). Here, we choose the hard threshold function which can be expressed as

$$T_\lambda(x, y) = \mathrm{sgn}(x).\max(0, |\,x\,| - |\,y\,|) \quad , \tag{4}$$

where, y is the threshold value.

In order to preserve primary reflections more effectively, a non-linear masking filter (Wang, 2003) is applied before the primary and multiple separation scheme, which can preserve most of primary energy denoted by $(1-\Phi)\bullet d$. In this way, only $\Phi \bullet d$ with multiples and some residual primary energy is involved in the following separation flow, with

$$\Phi_i = 1 - \frac{1}{\sqrt{1 + [\frac{A_{m\_i}}{WA_{d\_i}}]^{2M}}} \quad , \tag{5}$$

where, • denotes point-by-point multiplication, A_{m_i} and A_{d_i} are the amplitudes at sample i of the multiple model and the original dataset, respectively, M denotes the smoothing value, and W represents the weighting value.

Based on the above theory, the workflow for multiple subtraction in the CCT domain can be designed as follows:

- Apply the non-linear masking filter to preserve most of the primary events, and only the residual part is involved in the separation flow.
- Apply the LS matching to correct the overall amplitude and positioning errors.
- Transform the original dataset and the multiple model processed by the LS matching into the CCT domain. The residual primary energy can be recovered by solving eq. (3) by the threshold-based primary-multiple separation approach.
- Combine the recovered residual primary energy with the primary data preserved by the non-linear masking filter, to get the final primary output without multiples.

EXAMPLES

We first use a simulated data example to demonstrate the performance of the proposed approach. There are 101 shots and 101 receivers in this example. Each trace has 1000 time samples with 2 ms temporal sampling. Fig. 3a shows the original data, and the predicted multiple model is shown in Fig. 3b. Fig. 3c denotes the preserved primary energy by the non-linear filtering. The separated residual primary energy by the proposed approach is shown in Fig. 3d. Combining the data in Fig. 3c and Fig. 3d, the final de-multiple result is displayed in Fig. 3f. Comparing this with the primary energy obtained by the expanded multi-channel LS subtraction approach (Wang, 2003), for which we choose the space-time windows of size 101*21, it confirms the fact that the proposed approach maintains the event continuity and reduces the effective primary energy loss, as shown in the elliptical and rectangular areas in Fig. 3e and Fig. 3f. Similarly, the common offset profile contrasts in Fig. 4 also demonstrate the effectiveness of the proposed approach.

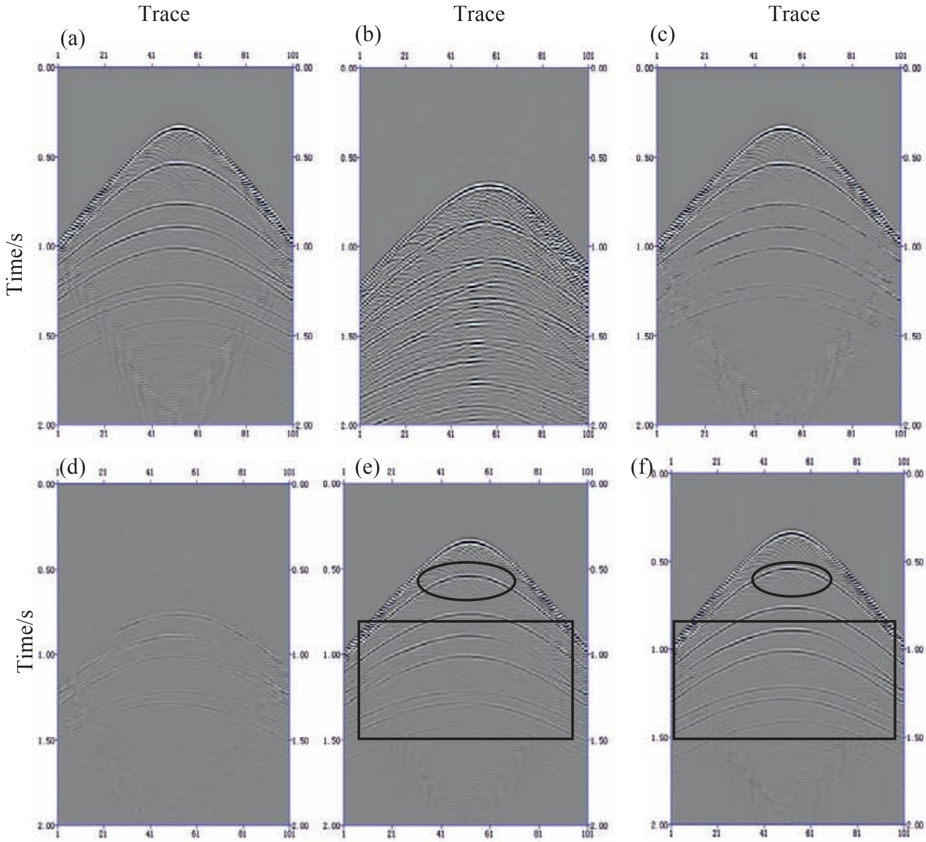

Fig. 3. Synthetic data example: (a) original shot gather, (b) predicted multiple model, (c) preserved primary data, (d) recovered residual primary data, (e) primaries recovered by expanded multi-channel LS subtraction, and (f) primaries recovered by the proposed approach.

Next, a 2D field marine dataset is used to illustrate the advantages of the proposed approach over that of the expanded multi-channel LS subtraction approach. The total shots are 432 with 314 receivers for each shot. There are 1751 time samples and the temporal sampling is 4ms. From Fig. 5a, we can see that the data is interfered with strong multiples, which seriously affects the identification of primary events. Fig. 5b denotes the predicted multiple model. Fig. 5c is the preserved primary by the non-linear masking filtering process. Fig. 5d represents the residual primary recovered by the proposed approach. Combining Fig. 5c with Fig. 5d, the final de-multiple result is obtained, as shown in Fig. 5f. Comparing this with the results derived from the expanded multi-channel LS subtraction approach in Fig. 5e (in this example, we use the space-time windows of size 53*27), it demonstrates that the proposed approach can recover the primary events better while we still observe residual multiple energy after the expanded multi-channel LS subtraction approach. From the near-offset profile displays, especially in the rectangular areas in Fig. 6, the same conclusion can also be reached that the proposed approach can suppress the multiples from middle-deep layers and protect the weak primaries.

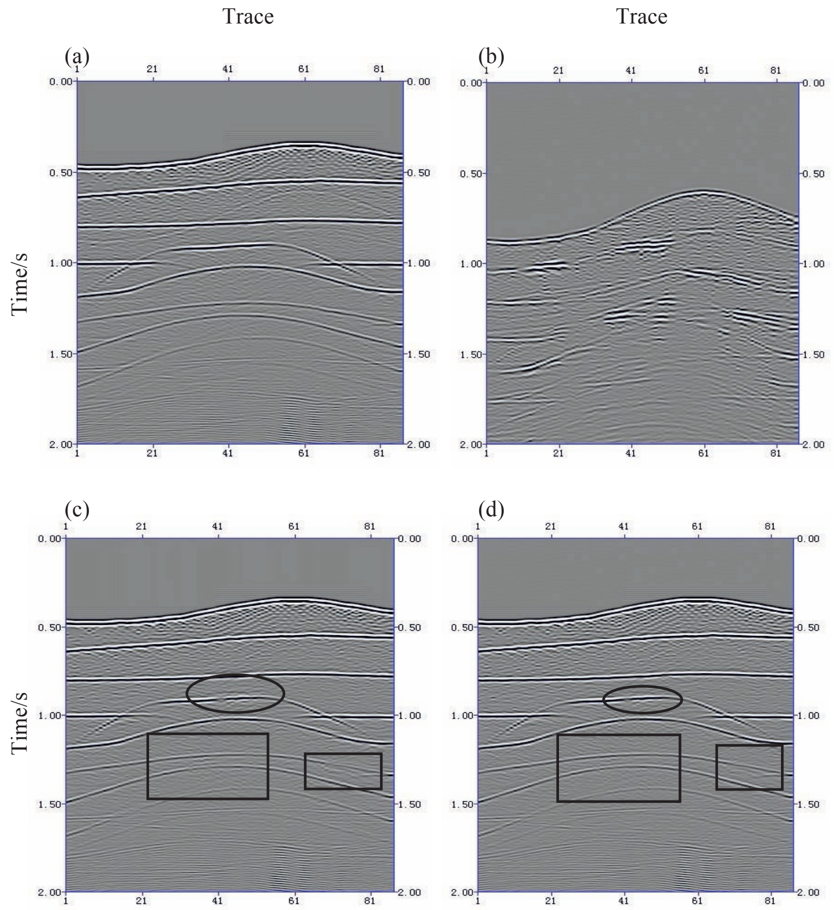

Fig. 4. Multiple subtraction results displayed in common-offset profiles: (a) original near-offset profile, (b) predicted multiple model, (c) primary data recovered by expanded multi-channel LS subtraction, and (d) primary data recovered by the proposed approach.

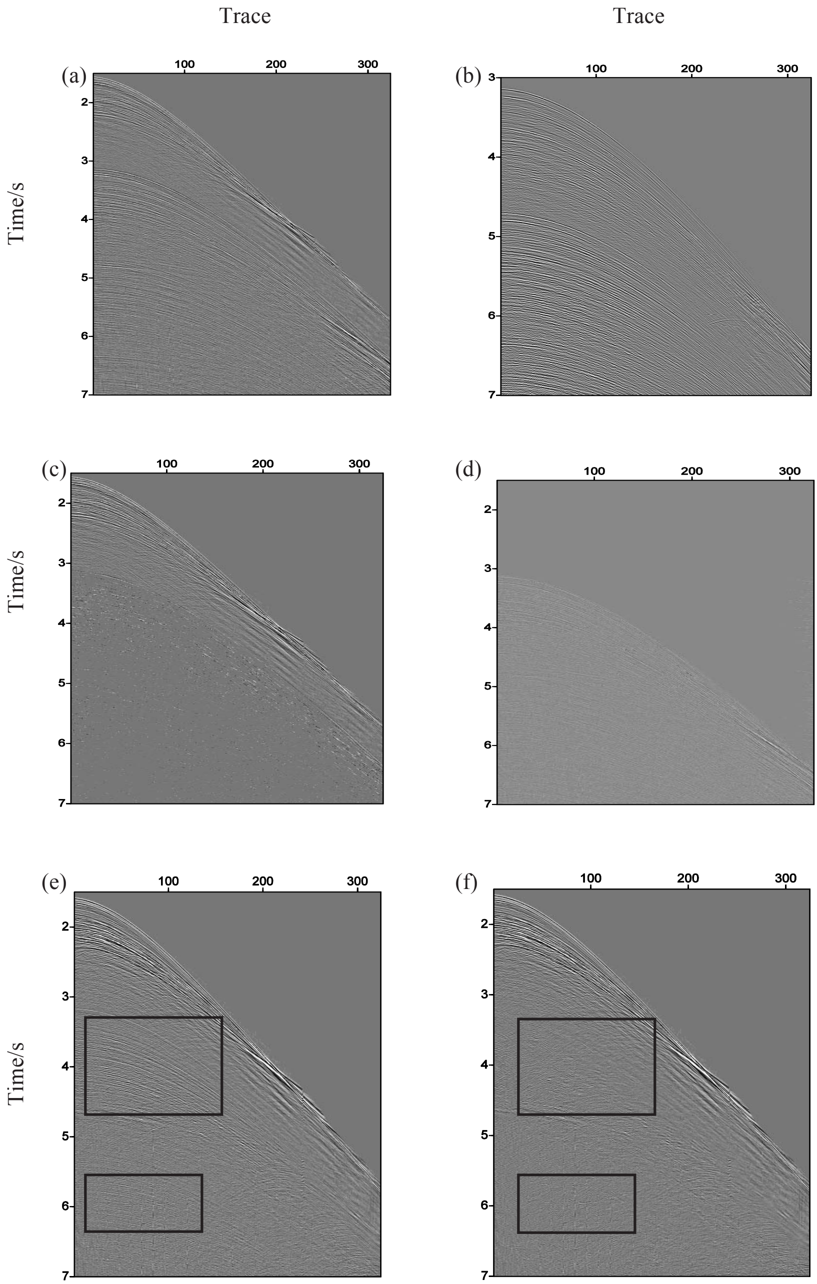

Fig. 5. Results for field data: (a) original shot gather, (b) predicted multiple model, (c) preserved primary data, (d) recovered residual primary data, (e) primaries recovered by expanded multi-channel LS subtraction, and (f) primaries recovered by the proposed approach.

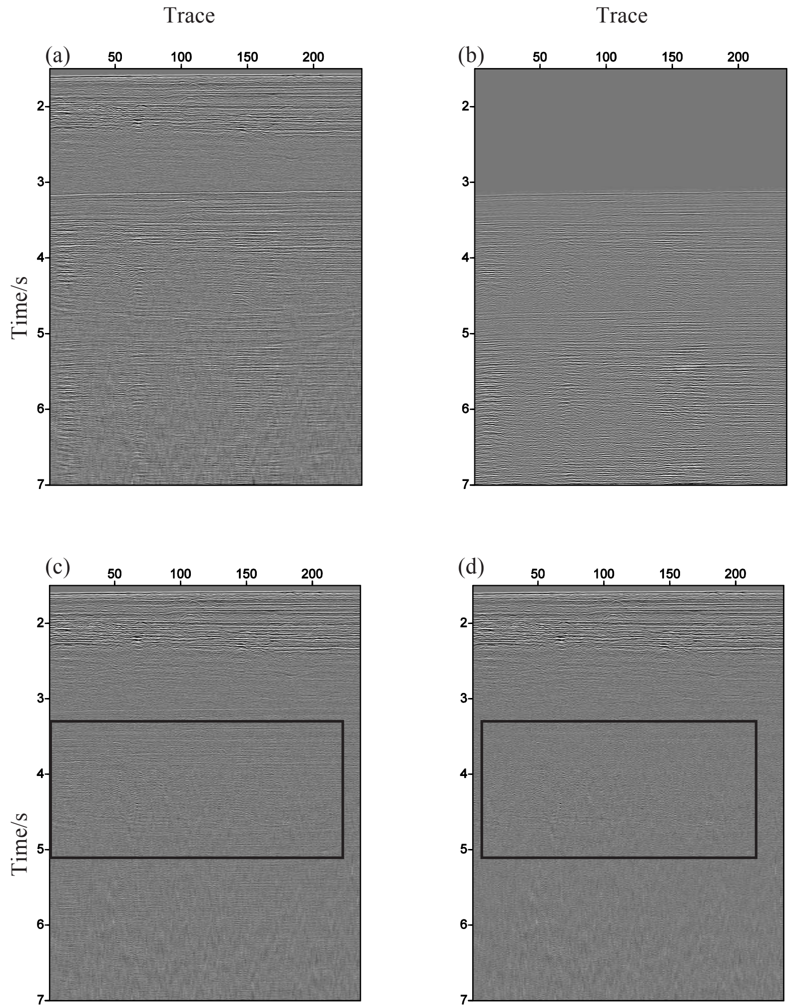

Fig. 6. Field data results in common-offset profiles: (a) original near-offset profile, (b) predicted multiple model, (c) primary data recovered by expanded multi-channel LS subtraction, and (d) primary data recovered by the proposed approach.

CONCLUSIONS

Conventional LS-based matching methods often fail to provide satisfactory results since non-stationary and some non-orthogonality exist between the predicted multiples and the primaries in the data. In this paper, we propose a primary and multiple separation approach by cascading the LS matching and a threshold procedure in the CCT domain. After a simple amplitude matching and global time shift correction via the LS matching, we can utilize the properties of the amplitude shift invariance of the CCT's coefficients to correct the residual misfit between the predicted multiples and the actual ones by a threshold-based de-multiple approach in the CCT domain. In order to protect primary events in an effective fashion, we apply a non-linear masking filter in advance, which can preserve most of the primary energy in the data separation process. Finally, we demonstrate through synthetic and field data that the proposed approach works quite effectively, and outperforms the expanded multi-channel LS subtraction.

ACKNOWLEDGMENTS

The authors would like to thank BGP for the permission to publish the work. We also thank Eric Verschuur for the constructive suggestions and recommendations that have strengthened the paper. Besides, we express the appreciation to the fund from the key laboratory of depositional mineralization and sedimentary mineral of the Shandong province.

REFERENCES

Candès, E.J. and Donoho, D.L., 2004. New tight frames of curvelets and optimal representations of objects with C2 Singularities. Commun. Pure Appl. Math, 57(2): 219-266.

Dong, L.Q., Li, Z.C., Yang, S.C., Wang, D.Y. and Wang, J., 2013. Non-causal matching filter multiple elimination method based correlation and iteration. Chin. J. Geophys. (in Chinese), 56: 3542-3551.

Fomel, S., 2009. Adaptive multiple subtraction using regularized nonstationary regression. Geophysics, 74(1), V25-V33.

Donoho, D.L., 1995. Denoising via soft thresholding. IEEE Transact. Informat. Theory, 41: 613-627.

Guitton, A., 2003. Multiple attenuation with multidimensional prediction-error filter. Expanded Abstr., 73th Ann. Internat. SEG Mtg., Dallas: 57-74.

Herrmann, F.J., Boeniger, U. and Verschuur, D.J., 2007. Nonlinear primary-multiple separation with directional curvelet frames. Geophys. J. Internat., 170: 781-799.

Herrmann, F.J., Wang, D.L. and Verschuur, D.J., 2008. Adaptive curvelet-domain primary-multiple separation. Geophysics, 73(3): A17-A21.

Kumar, V. and Herrmann, F.J.. 2009. Incoherent noise suppression with curvelet-domain sparsity. Expanded Abstr., 79th Ann. Internat. SEG Mtg., Houston: 3356-3359.

Lu, W.K., 2006. Adaptive multiple subtraction using independent component analysis. Geophysics, 71(5): S179-S184.

Neelamani, R., Baumstein, A.I., Gillard, D.G. and Hadidi, M.T., 2008. Coherent and random noise attenuation using the curvelet transform. The Leading Edge, 27: 240-248.

Neelamani, R., Baumstein, A.I. and Ross, W.S., 2010. Adaptive subtraction using complex-valued curvelet transforms. Geophysics, 75(4), V51–V60.

Rayan, S., Wang, D. L., Yilmaz, O. And Herrmann, F.J., 2007. Curvelet-based primary-multiple separation from a Bayesian perspective. Expanded Abstr., 77th Ann. Internat. SEG Mtg., San Antonio: 2500-2504.

Verschuur, D.J., Berkhout, A.J. and Wapenaar, C.P.A., 1992. Adaptive surface-related multiple elimination. Geophysics, 59: 1166-1177.

Verschuur, D.J. and Berkhout, A.J., 1997. Estimation of multiple scattering by iterative inversion, Part Ⅱ: Practical aspects and examples. Geophysics, 62: 1596-1611.

Wang, Y., 2003. Multiple subtraction using an expanded multi-channel matching filter. Geophysics, 68: 346-354.