Deblending of continuously recorded OBN data by subtraction integrated with a median filter

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Summary

Much attention has been drawn toward simultaneous sources recently, primarily due to the potential cost saving when efficiently acquiring high quality seismic data. Compared with conventional streamer acquisition, Ocean Bottom Node (OBN) data has some benefits by utilizing full azimuth and multi-component information recorded by both hydrophone and geophone. Here we present a deblending scheme that harnesses subtraction incorporated with a median filter to separate simultaneous sources OBN data. Our approach is data-driven by extracting the noise model from the blended input, and provides a solution that converges quickly to its limit in removing interfering energy.

Introduction

Blended sources recording is a promising technology, with a potential future associated with ocean bottom seismic acquisition. Cost saving related to this acquisition is realized by speeding up the shot rate and reducing the survey duration by half or more at the expense of a modestly higher daily operation for an additional vessel. The deblending problem can be approached from a denoising perspective by applying the time delay shift to switch between primary and secondary source domains, assuming that the primary source fires at a predetermined time and the secondary source at a random dithering time. Such a problem becomes more interesting and challenging as primary and secondary sources fire more stochastically, say within the record length of the 1st source shoots, instead of firing the 2nd source, we randomly exploit the 1st, 2nd or even both sources to generate the blended data. To address this challenge, we have designed a novel deblending flow through subtraction integrated with a median filter, resulting in high quality deblended products.

There are two main categories of approach when processing simultaneous sources data. One is an active separation method that involves inversion, for instance, sparse radon inversion or curvelet subtraction under compressive sensing. Alternatively, the passive approach starts from pseudo-deblended data, where blending noise becomes incoherent by switching to the other source domain. Thus the deblending problem transforms into a denoising one, and many signal processing tools become available. Iterative estimation subtraction (Mahdad, et al., 2011) and enhanced adaptive subtraction (Liu, et al., 2014) are such examples. Our method belongs to the passive category.

In the processing of OBN data, besides the techniques of directional deconvolution, wavefield separation, crossline wavefield reconstruction and converted-wave processing, efforts have been put onto multi-component denoise as well. For example, processors can convert the pressure data to its equivalent velocity data and suppress noise from signal cooperatively (Peng, et al., 2014). Here we present results of the pressure data, and deblending in other components recorded by geophone can be accomplished by utilizing our flow and multi-component denoise without much difficulty.

Methodology

Two important steps exist in our deblending process: step 1, construct and subtract a noise model. Since OBN data is recorded continuously for certain days by using autonomous nodes on the seafloor, the relative shot epoch time is calculated first, and candidates (in one receiver station) that fall into one record length of the current trace's shot epoch time are selected. Then the epoch time difference between any given shot and every selected shot is computed and applied before summing all the interfering traces to obtain the noise model (see figures 1a-1b). Step 2, apply a residual noise suppression filter.

Let D, I_1, I_2, S_1, S_2, N_1 and N_2 be the recorded nodal data, blended source 1, blended source 2, unblended source 1, unblended source 2, interfering energy that comes from source 1, 2 or both firing within one record window of source 1, similarly for source 2, respectively. We have

$$D = I_1 + I_2 \tag{1}$$
$$I_1 = S_1 + N_1 \tag{2}$$
$$I_2 = S_2 + N_2 \tag{3}$$

A median filter is employed to clean up the raw input that will be fed into creating the noise model. In the following formulas, f represents the median filter, i denotes the source index $(1, 2$ in our case$)$, $I_i(n)$ stands for the n^{th} iterative output, $\Delta(m)N_i$ means the residual blended energy after m^{th} iteration, G_{I_i} extracts interfering traces with needed time shift applied based on input and difference of shot epoch time, and $\sum$ sums all the shifted extracted traces to build the noise model. In the k^{th} iteration

$$f(I_i(k-1)) = S_i + \Delta(k)N_i \tag{4}$$
$$I_i(k) = I_i - \sum G_{I_i}\{f(I_1(k-1)), f(I_2(k-1))\} \tag{5}$$

Then a residual noise suppression filter is applied. Since most blended energy has been attenuated, the remaining blended noise has a more intrinsically random characteristic, and can be removed with a moderate threshold in the filter. During processing, data is sorted in receiver order which is perpendicular to common shot gather to randomize the blending interference and make it appear as spikes.

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Our strategy focuses more on building a high fidelity noise model by developing a feasibly iterative scheme. The integrated median filter mainly helps to enhance the accuracy of the model as the filtered noise could be signal if switching to the other source domain. This method is implementable in production since it only takes very few rounds of iterations to reach a suitable model.

Field Data Results

This approach was tested on a 3D OBN dataset in the Gulf of Mexico Shelf Region. Two vessels were deployed in the acquisition, each equipped with two air guns. The source-line spacing and shot-point interval are 50 x 50 m, with receiver-line spacing and station interval 500 x 200 m.

The following figures 1a-1b show the micro perspective of our deblending process, where we illustrate how a single blended trace is being processed in the step 1 that removes most of the blended energy.

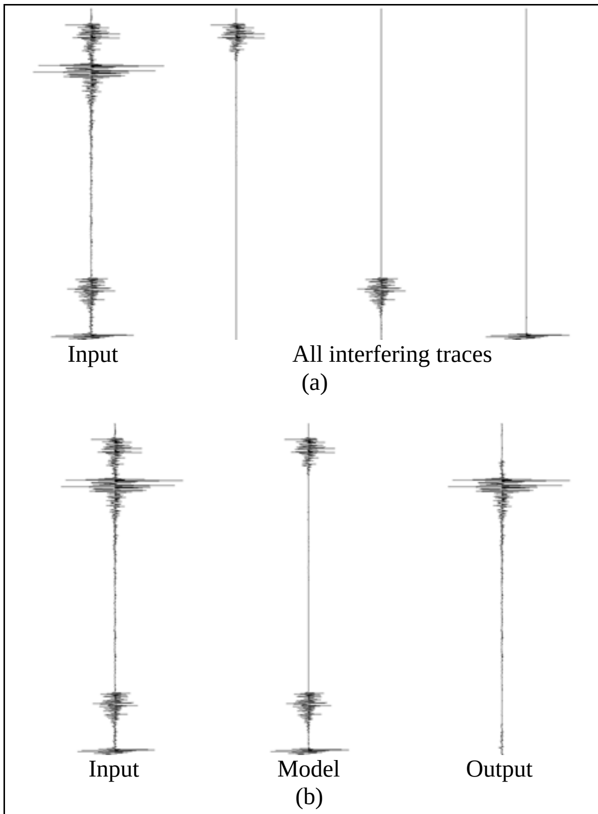

Figure 1*: (a) Blended trace and all the interfering traces based on the search criterion with shot epoch time difference applied; (b) Blended trace, noise model and subtraction output*

Figure 1a presents one single blended trace and the rest as interfering traces with necessary time shift applied. Figure 1b lays out the blended trace, noise model that summed all the shifted extracted traces, and subtraction output.

On the next page, figures 2a-2f display data on a macro viewpoint. The necessity for the second iteration becomes apparent because one iteration hurts coherent structure in some areas and additional improvement from the residual noise suppression filter is observable. As mentioned in (Peng, et al., 2013), the leakage energy oscillates during the iterative cycle: with odd iterations more inclined to attenuate interfering noise and even iterations favoring coherent energy. The subtraction is designed to stop after two iterations as most of the blending noise has been attenuated, while preserving more coherent energy. Our approach is efficient in terms of the number of iterations and the reasonable result obtained. The residual noise attenuation filter works fairly well afterward.

Figures 2a-2f exhibit the common receiver gather of (a) Blended data; (b) First iteration; (c) Second iteration; (d) Residual noise removal filter applied; (e) Difference between blended data and the second iteration (to confirm that signals are not damaged); (f) Difference between the second iteration and residual noise removal filter applied.

For QC purposes, the data has been resorted to shot domain where cross terms (interference) have coherent structure as well. Figures 3a-3c show data in shot domain of (a) Blended data; (b) Deblended data; (c) Difference between (a) and (b). We include migrated images at the same stages in figures 4.

Conclusions

We have developed a method that synthesizes subtraction and median filter to separate simultaneous sources data and reconstruct the deblended primary and secondary shot simultaneously for OBN data. This method is applicable to large-scale datasets because of its fast convergence speed (usually two iterations can produce high quality outcomes) and can be extended to three or more vessels in a straightforward manner. The reconstructed deblending data demonstrates our technique is effective even when primary source and interfering noise share visible overlapping areas.

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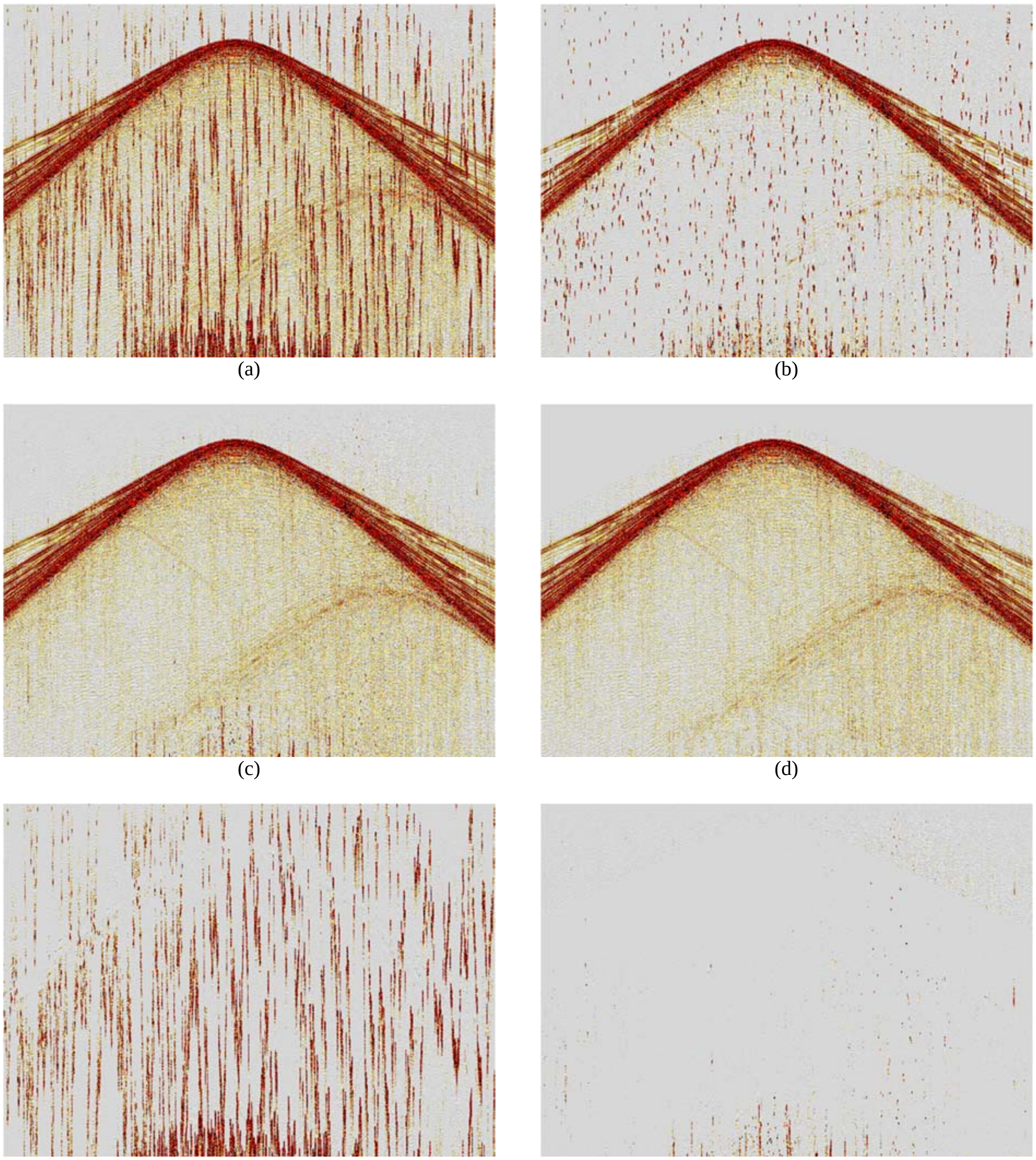
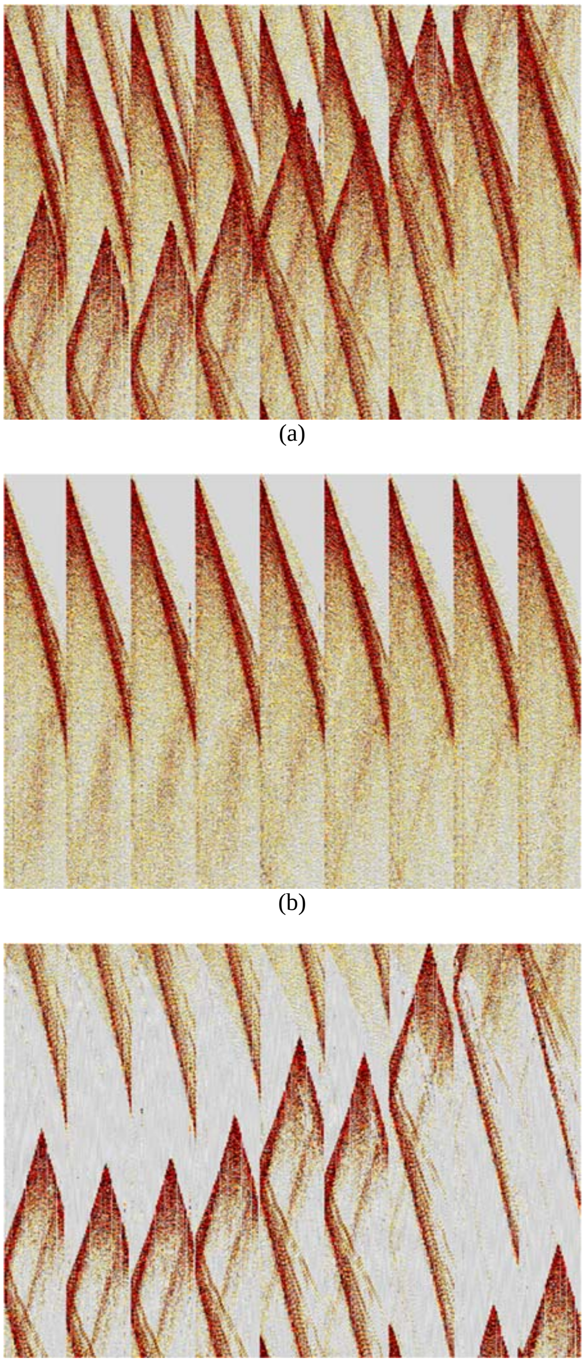
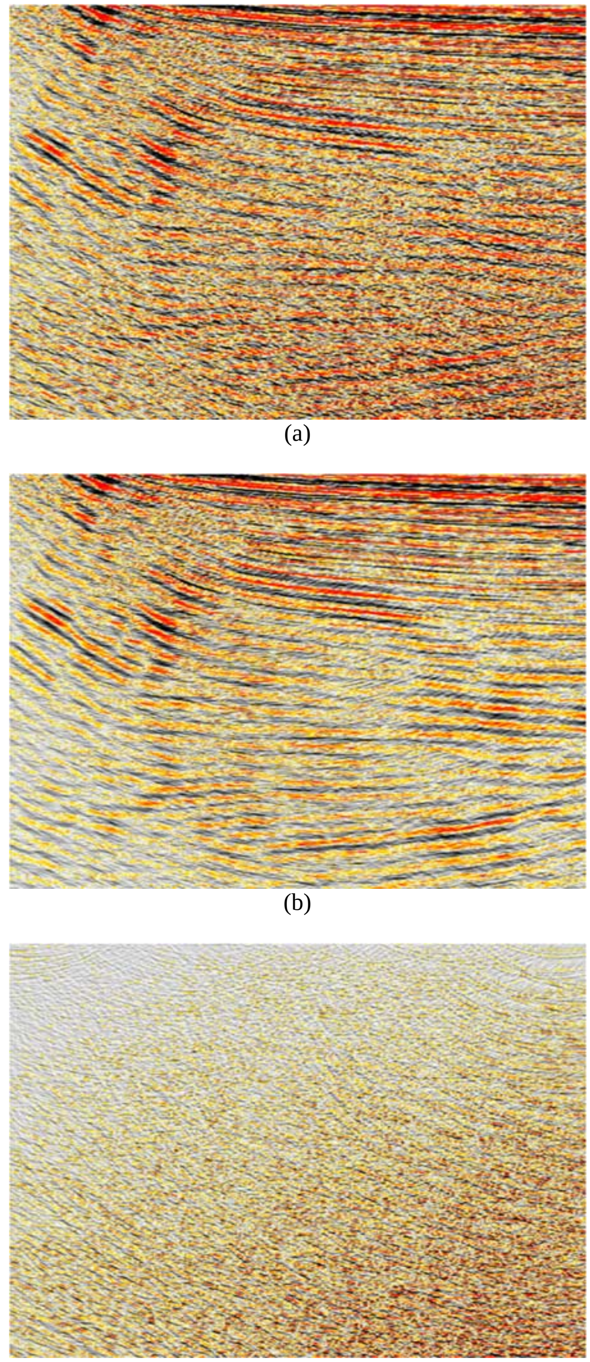


Figure 2: Comparison in the common receiver gather of the following (a) Blended data; (b) First iteration; (c) Second iteration; (d) Residual noise removal filter applied; (e) Difference between (a) and (c); (f) difference between (c) and (d)



(a) (b) (c)

***Figure 3**: Comparison in shot gather of (a) Blended data; (b) Deblended data; (c) Difference between (a) and (b)*



(a) (b) (c)

***Figure 4**: Comparison in migrated image of (a) Blended data; (b) Deblended data; (c) Difference between (a) and (b)*

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EDITED REFERENCES

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