A Robust Iterative Deblending Method for Simultaneous Source Acquisition

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Summary

This paper presents a new method for simultaneous source deblending developed in the context of spatial coherency preservation. The deblending is formulated as an inverse problem which is solved in local overlapping windows extracted from the blended data. To constrain the solution, the unknown sources are assumed to be quasi-predictive in the spatial domains. During the signal estimation, this will promote tolerance on impulsive blending noise and provide flexibility and robustness in coherency preservation depending upon the signal to noise ratio at a given frequency or within a given window. The proposed method is generic and can be applied to all configurations of simultaneous source acquisition and can deal with an arbitrary number of sources. Tests on numerically blended real towed streamer marine data show good deblending results with an excellent compromise between signal preservation and cross-talk contamination across a wide frequency range, particularly towards the low end. The proposed method is robust and flexible and can be applied in the early stages of a typical marine seismic processing sequence.

Introduction

In simultaneous source acquisition, seismic data is often recorded with an overlap between successive shots which are fired using controlled randomized dithering times. It can have a variety of configurations such as simultaneous long offset (van Borselen and Baardman, 2012) or simultaneous triple-source (Long, 2017). Compared to conventional acquisition, simultaneous source acquisition achieves an improved operational efficiency and may offer better sampling of the data in terms of fold, azimuth and/or offset distributions. However, these benefits can only be realized if the recorded data, with interfering energy from multiple sources, can be separated into the individual sources via deblending.

In this abstract, we propose a new robust, multi-domain iterative method for deblending seismic data acquired in a generic simultaneous source acquisition. The method inverts for the sources by minimizing a least squares cost function with coherency constraints. The coherency measure is based on the spatial quasi-predictability of seismic events in the frequency domain. Different spatial dimensions are considered in cascade in order to explore all the potential coherency in the data. Given the impulsive characteristics of the cross-talk, we modified the coherency measure to make it robust for cases of poor Signal to Noise Ratio (SNR). The proposed method is tested on a numerically blended real dataset where the signal energy to blending energy ratio is about -30 dB (at 60 Hz, see Fig. 1). The method shows very good results in recovering the primary source. The proposed method is data-driven to a large extent and requires minimal parameter testing.

Theory

Deblending strategies have often been formulated as an optimisation problem with coherency (van Borselen and Baardman, 2012) or sparsity (Duan et. al, 2017) constraints in a domain where the energy from the secondary sources will appear as incoherent blending noise. The particular challenge of successful deblending lies in the overlapping zone (Fig. 1), where the energy from the consecutive shots appears as the impulsive blending noise to the signal of the current shot when sorted in any domain orthogonal to the shot domain, such as common channel, common receiver or common mid-point domain. The deviation of the blending noise statistics from the Gaussian assumption renders any coherency measure biased and no longer effective. Consequentially the deblending result will contain significant cross-talk which will need to be removed by a post-deblending filter. Robust f-x based filters, such as the one proposed by Chen and Sacchi (2014), are effective only when the underlying signal is strong. This is often not the case as the general desire is to extend the useable record length.

This paper proposes to adapt the quasi-predictability coherency constraint and achieve deblending by solving the minimization problem in the frequency-space domain. Consider one frequency slice of the data and denote it by $D = (d_1, \ldots, d_N)$ where N is the number of spatial traces in the processing window. The deblending problem is then formulated as follows:

$$\min_{S_k} \left(\left\| D - \sum_{k=1}^{K} H_k S_k \right\|_2^2 + \sum_{k=1}^{K} \mu_k \|A_k S_k\|_2^2 \right). \tag{1}$$

Here, the subscript $k \in [1, K]$ denotes the source index, out of the total K sources to be estimated; H_k is a diagonal matrix representing the time-shift in the frequency domain subject to the time dither of the kth source S_k; A_k is the projection error fitting matrix associated with S_k (Chen and Sacchi, 2014) and μ_k is a robustness scalar which increases (to enhance coherency) when the SNR in $(H_k)^T D$ decreases. In reference to the work by Chen and Sacchi (2014) where a Hilbert cost function is used in the regularization term, we found that this approach is not enough to remove the crosstalk in a deblending problem with real data. Beside this, the estimation of the projection filter coefficient requires additional time due to the non$-L_2$ regularisation term. Matching the scaler μ_k to the SNR in $(H_k)^T D$ not only provides the required robustness in real applications, but also enables a fully automatic processing sequence with minimal testing. The numerical solution of the objective function in equation (1) can be achieved using an iterative algorithm with an estimation phase to compute the projection filter's coefficients from the current estimation of each source, and a prediction phase to update the estimated sources according to the objective function in equation (1). The coefficients of the projection filters are

estimated using a methodology similar to the one described by Sacchi and Kuehl (2001). The robustness scalars μ_k are updated after each iteration using a measure of the SNR based on the wavenumber contents at every frequency slice. Depending on the sorting domain or the value of the constant NMO velocity used to flatten the data, the above iterative process is repeated with the input being the residual blended data. The process is repeated with an aggregate accumulation of all estimated sources until the residual is small. It is worth mentioning that alternating different domains is key to achieving a considerable decrease of the blended energy.

Examples

The method has been tested in a controlled manner using numerically blended data to simulate a triple-source acquisition. The P-UP data from a recent dual-sensor dual source 3D survey in the Potiguar Basin, north-east of Brazil was used as the reference. As shown in Figure 1, to generate the blended data (Fig. 1b), we numerically blended the current shot record (Fig. 1a) with the dithered consecutive shot record using a dither time table from our triple-source acquisition. The dither time gives a realistic clean record length of approximately 6.5 seconds with a controlled randomized dither variation to facilitate deblending and acquisition efficiency requirements. This mimics the most challenging deblending issues related to deepwater simultaneous triple-source acquisition where in the highlighted overlapping zone, the signal energy to blending energy ratio is typically about -30 dB to -20 dB.

Figures 2a and 2b present the data before and after the deblending. Before the deblending process, the blending noise is orders of magnitude stronger than the signal. Even with the raw data in such an early stage of the processing, the proposed method gradually attenuates the crosstalk energy to the level of the background noise over the iterations and drives the deblended estimates in Fig. 2b towards the desired solution in Fig. 2c. At the end of the deblending process, within the level of background noise, the deblended result recovers the unblended reference data in Fig. 2c.

To further verify the performance of the proposed method, we stack the raw data and deblended data as shown in Figures 3a and 3b, respectively. After the deblending, the blending noise associated with the direct arrival of the subsequent source is removed with the signal well preserved. To analyse the results in the strong interference region as highlighted in Figures 3a and 3b, the zooms of the figures are presented in Figures 4a and 4b. In the shallow section (blue circles), one might carefully observe the signal hidden behind the overlapping shot energy even before the deblending, whereas for the region with a strong energy overlap (red boxes), the proposed method effectively removed the crosstalk and retrieved the underlying hidden signal which is very weak compared to the overlapping energy.
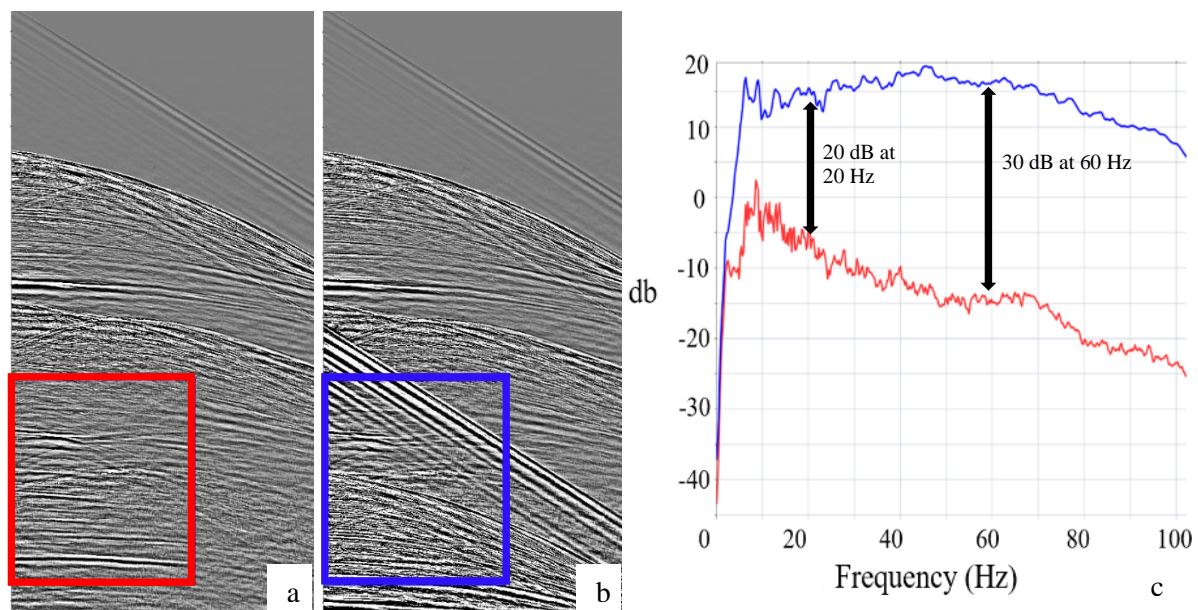

Figure 1 a: unblended shot, b: numerically blended shot, c: amplitude spectra of the highlighted regions.
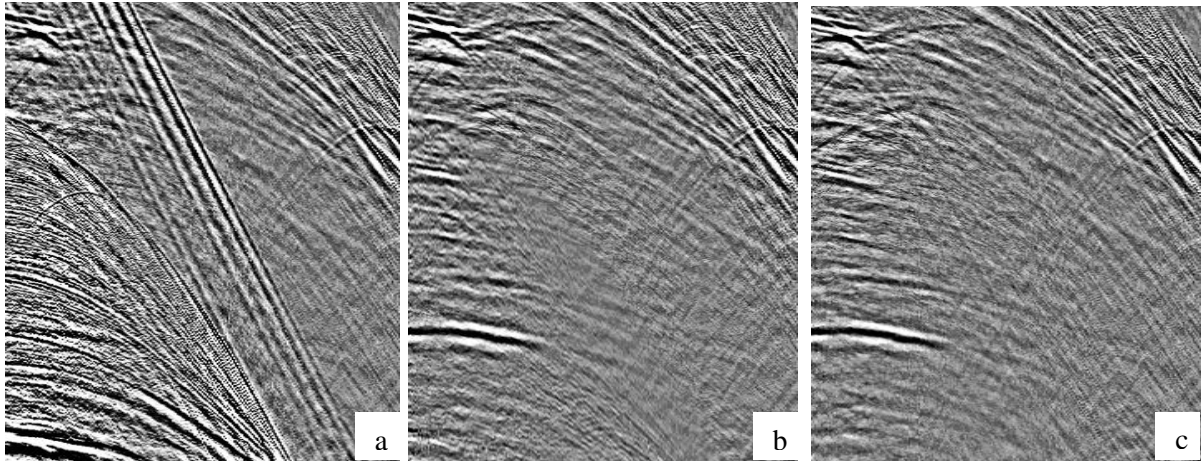
Figure 2 a: zoom-in overlapping section before deblending, b: same section in 2a after deblending for the current shot, c: reference section before the data were blended in processing for this test.
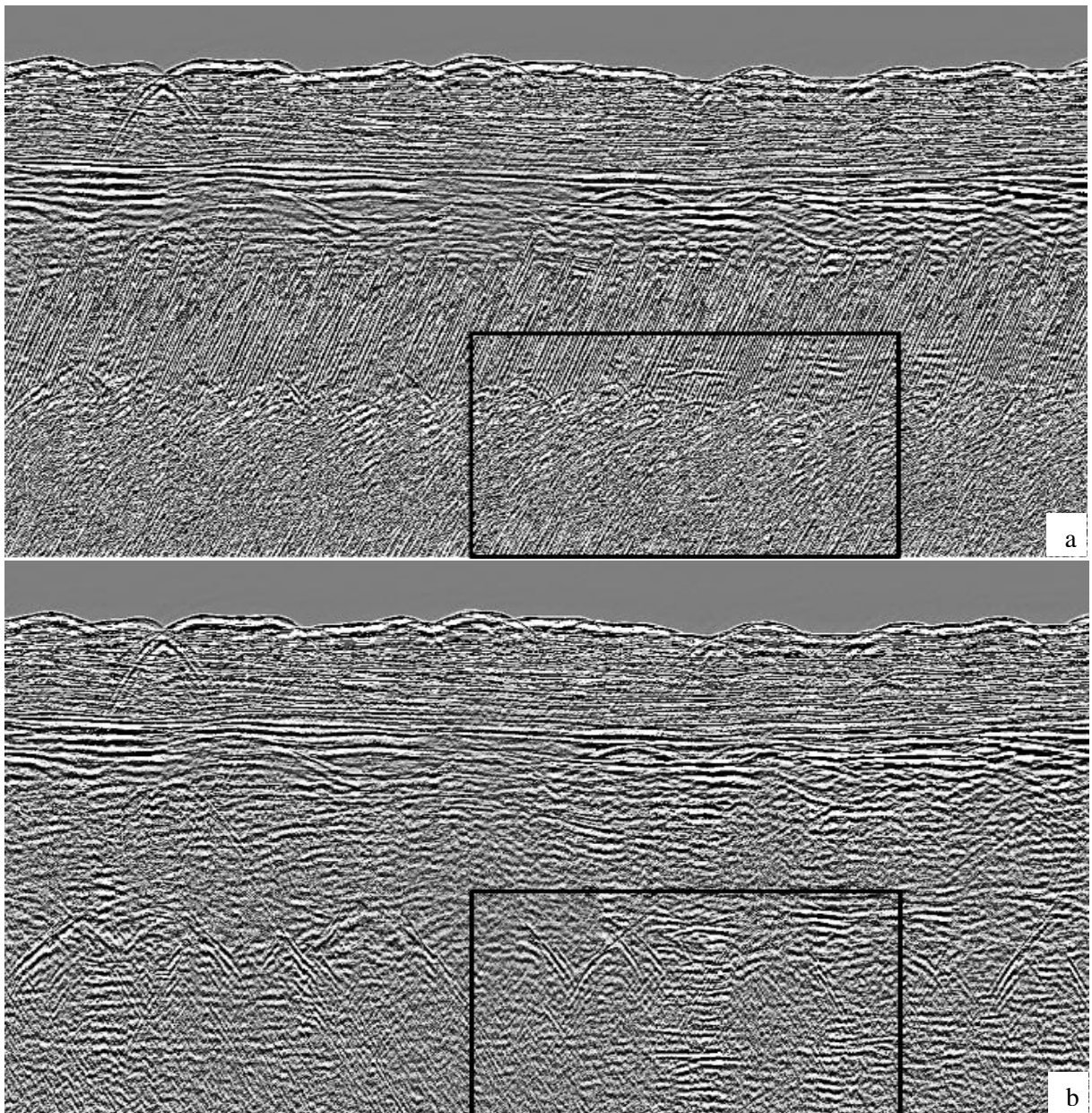

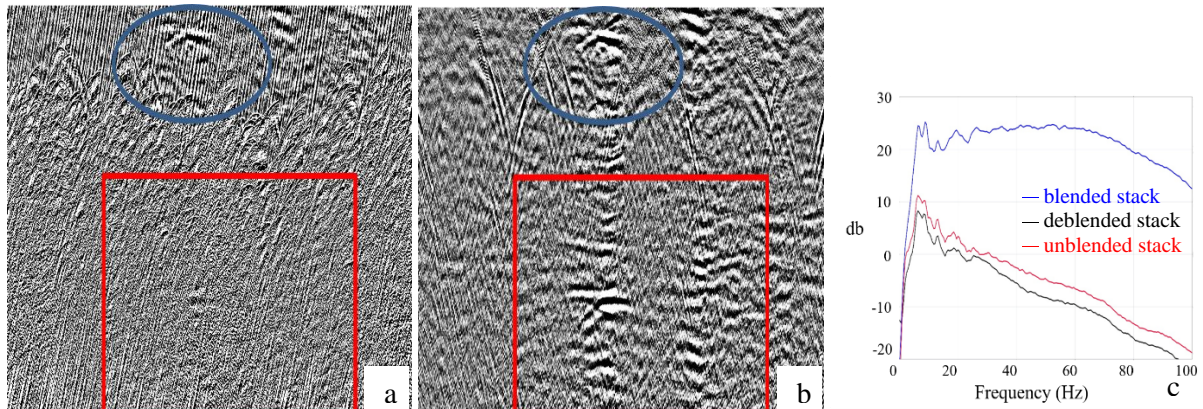*Figure 3 a: stack before deblending, b: stack after deblending.*

Figure 4 a: zoom-in section of the highlighted area in Fig. 3a before deblending, b: zoom-in section (same section as in 4a) as highlighted in Fig. 3b after deblending, c: the spectrum analysis of the sections in 4a and 4b and the same section on the stack using the unblended data.

Figure 4c shows the amplitude spectrum analysis of the data windows from the stacks of the unblended data (control), from before (Fig. 4a) and after (Fig. 4b) the deblending process. The data before deblending is dominated by the strong blending noise that represents the primaries from the subsequent shot. After the deblending process, the amplitude spectrum becomes more balanced; particularly at low frequencies, and its shape is almost identical to the unblended data.

Conclusions

The popularity of triple-source acquisition and the likelihood of surveys being acquired with still more sources (e.g. penta-source or hexa-source) presents the problem of retaining fold and clean record length whilst maintaining sufficient water speed for full control of the towed streamer spread. The widespread use of continuous recording systems now enables the trace length to be a processing parameter rather than a function of the acquisition configuration. The successful deblending of the multiple sources in a robust and efficient manner is a formidable challenge. In this paper we propose to use the quasi-predictability as coherency constraints to construct an iterative deblending solution that runs in a cascade mode with alternating data sorting. The formulation of the proposed method is generic and can handle all configurations of simultaneous acquisition and with an arbitrary number of sources. Application of the proposed method on numerically blended triple-source towed streamer data shows good results in terms of reducing the crosstalk while preserving the signal and its frequency content.

Acknowledgements

References

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