A Practical Method for Multi-source Deblending Using Spatio-temporal Compressive Sensing

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Summary

This paper presents a new method for simultaneous source deblending developed in the context of compressive sensing. The deblending solution is formulated as an inverse problem which is solved in local overlapping spatio-temporal widows extracted from the blended data. To constrain the solution, the unknown sources are assumed to have a reduced rank with minimal nuclear norm. This will promote the sparsity of seismic data without relying on the use of a given data decomposition method such as a Fourier or curvelet transform. In our case, the decomposition is data-driven which arguably would lead to better data modeling and therefore a better source separation. The proposed method is generic and can be applied to all configurations of simultaneous shooting. Test results on triple-source data show a good deblending quality which preserves the frequency content of the data after separation. The proposed method is robust to acquisition noise such as swell allowing it to be flexibly applied at early stages of a typical marine seismic processing sequence.

Introduction

In simultaneous source acquisition, seismic data is recorded with an overlap between successive shots. Dithering the fire time of shots is the key feature of this type of acquisition. It has a variety of configurations such as simultaneous long offset (Van Borselen and Baardman, 2012) or simultaneous triple-source (Beitz et. al, 2016). Compared to conventional acquisition, simultaneous shooting achieves better sampling of the data in terms of fold, azimuth and/or offset distributions. In addition, this acquisition has an improved operational efficiency which lowers the cost of a survey. 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 method for deblending seismic data acquired in a generic simultaneous shooting survey. The method inverts for the sources in a framework of compressive sensing using a spatio-temporal modelling of the sources constrained with low-rank matrix approximation. The proposed Low-Rank DeBlending solution (LRDB) fits any configuration of simultaneous source acquisition and is very robust to acquisition noise such as swell, which makes it a flexible solution that can be deployed at an early stage of a typical marine processing sequence.

Theory

For a blended data $D(t,\widetilde{x_s},\widetilde{x_r})$ consisting of n individual unblended sources $D_i^u(\tau,\widetilde{x_s},\widetilde{x_r})$ with source location $\widetilde{x_s}$ and receiver location $\widetilde{x_r}$ at time t, the blending process can be formulated as:

$$D(t,\widetilde{x_s},\widetilde{x_r}) = \sum_{i=1}^{n} \int_{-\infty}^{\infty} \delta(t-\Delta t_i-\tau) D_i^u(\tau,\widetilde{x_s},\widetilde{x_r})\, d\tau, \qquad (1)$$

where the subscript i denotes the source index from 1 to n , Δt_i is the dither time associated with the i^{th} unblended source and τ is the pseudo time.

In the case of a perfect acquisition which distributes the energy of each unblended source into completely separable parts of the blended data. The deblending problem, i.e. the inverse problem of data blending in Eq. (1), is no more than a series of truncations. However, our acquisition is always restricted by the safety, environmental or economic factors which make the energy from one source overlap with the others either temporally as in the simultaneous long offset configuration or spatially as in the more recent triple-source configuration (Beitz et. al, 2016). In both cases successful deblending is crucial to a high quality seismic end product.

Deblending strategies have always been formulated as an optimisation problem with the aim to preserve signal. The differences are mainly in the types of constraint used for the unknown source (Van Borselen and Baardman, 2012) or the type of solver (Kumar et. al, 2015). On the other hand, the performance of the signal preservation is highly depended on the domain and the bases used for the data reconstruction. We thus propose to use data-driven bases and factorization-based formulations as in a compressed sensing setting and solve the following rank (nuclear-norm) minimization problem:

$$\min_{L_i,\,R_i} \sum_{i=0}^{n} \left\| L_i(f,\widetilde{x_s},\widetilde{x_r}) R_i^H(f,\widetilde{x_s},\widetilde{x_r}) \right\|_* \text{ such that } \left\| D(f,\widetilde{x_s},\widetilde{x_r}) - \sum_{i=1}^{n} e^{-2\pi i\omega\Delta t_i} L_i R_i^H \right\|_2 \le \sigma. \quad (2)$$

Here, each deblended source in the Fourier domain $D_i(f,\widetilde{x_s},\widetilde{x_r}) = L_i(f,\widetilde{x_s},\widetilde{x_r}) R_i^H(f,\widetilde{x_s},\widetilde{x_r})$ is represented by the product of two low-rank matrices, where the superscript H denotes the Hermitian transpose, $L_i \in \mathbb{C}^{n_r\times n_f\times\gamma}$ and $R_i \in \mathbb{C}^{n_r\times n_s\times\gamma}$ contain the factorization bases, n_r denotes the number of receivers, n_f denotes the number of discrete Fourier slices, n_s denotes the number of sources, $\gamma \ll \min(n_s,n_f)$ is a scalar measurement of the matrix rank and σ is the target data misfit tolerance.

A recent rank-minimization based deblending method (Kumar et. al, 2015) performs deblending in each frequency slice where an explicit low-rank assumption is made on some spatial domain. In real acquisitions, the spatial sampling rate is never as fine as in time. This assumption would thus not be valid beyond a low frequency threshold. On the other hand, as the dither time is completely transferable to the frequency information and the blending operation is periodic along the frequency axis, the low-rank assumption on the spatio-temporal windows in our LRDB is always valid.

To solve the basis pursuit denoise (BPDN) problem in Eq. (2), following Aravkin et. al, 2012, we employ an extended SPGl1 solver (Berg and Friedlander, 2008) and instead solve a sequence of Least Absolute Shrinkage and Selection Operator (LASSO) subproblems by updating τ via the Newton's method on a Pareto curve as follows:

$$\min_{L_i,\,R_i} \left\| D(f,\widetilde{x_s},\widetilde{x_r}) - \sum_{i=1}^{n} e^{-2\pi i\omega\Delta t_i} L_i R_i^H \right\|_2 \text{ such that } \sum_{i=0}^{n} \left\| L_i(f,\widetilde{x_s},\widetilde{x_r}) R_i^H(f,\widetilde{x_s},\widetilde{x_r}) \right\|_* \leq \tau, \quad (3)$$

or using the nuclear norm relationship found in Rennie and Srebro, 2005, more practically solve

$$\min_{L_i,\,R_i} \left\| D(f,\widetilde{x_s},\widetilde{x_r}) - \sum_{i=1}^{n} e^{-2\pi i\omega\Delta t_i} L_i R_i^H \right\|_2 \text{ such that } \sum_{i=0}^{n} \frac{1}{2} \left\| L_i(f,\widetilde{x_s},\widetilde{x_r}); R_i(f,\widetilde{x_s},\widetilde{x_r}) \right\|_F^2 \leq \tau, \quad (4)$$

where $\|\cdot\|_F$ denotes the Frobenius norm. Comparing to Eq. (3), the LASSO problem in Eq. (4) performs the sparsity constraint directly on the factorization bases via rescaling without explicit data reconstruction or singular value decomposition and is thus more efficient.

Examples

Figure 1a shows the configuration of a recent triple-source acquisition from offshore Malaysia (Fig. 1b). Three guns are fired consecutively and sequentially with a random dither time. The firing interval is much less than a conventional 12s and the dither times are optimised to meet both HSE and economic expectations (Beitz et. al, 2016). This configuration improves crossline sampling and more importantly acquisition efficiency compared to conventional dual source acquisition since streamer spacing may be increased. On the other hand, a typical shot for deblending, in Fig. 2a, contains data from all three individual guns with large overlaps both at the beginning and the end of conventional recording duration. LRDB is applied to recover a conventional 12s record for each source.

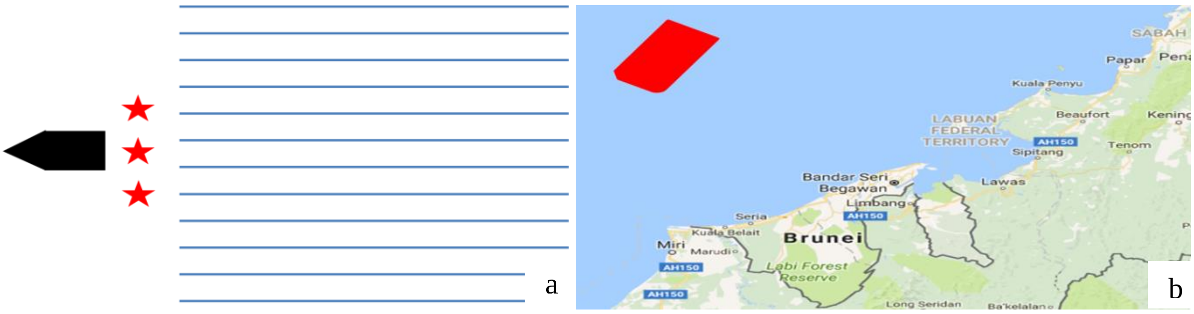

Figure 1 *a: Demonstration of the towing profile, vessel, guns and streamer cables are indicated in black, red and blue, respectively, b: Survey Map.*

Figures 2b, 2d and 2e present the highlighted region in Fig. 2a before and after the deblending applied on a raw hydrophone data. At the beginning of the LRDB iterations, the crosstalk is orders of magnitude stronger than signal. Even with raw data in such early stage of the processing, LRDB gradually attenuates the crosstalk energy to the level of the background noise over the iterations and drives the deblended estimates in Figs. 2d and 2e toward the desired solution. The convergence is also confirmed by the normalised data misfit plot in Fig. 2c. In solving each LASSO problem in Eq. (4), the convergence rate is steepest at first and then becomes gradual. With the updated τ and enlarged solution space, the consecutive LASSO problem continues its efficient converge to meet the target data misfit tolerance and sparsity in the BPDN problem in Eq. (2).

To further verify the performance of LRDB, we stack the raw data up to 12s. Blended and deblended crossline stacks are shown in Figs. 3a and 3b, respectively. Before the deblending the direct arrival of the subsequent source interferes with the signal of the previous source as early as 6s while its strong refection energy as blending noise covers the signal between 7.5s and 12s completely (highlighted area). After the LRDB, the crosstalk associated with the direct arrival of the subsequent source is removed with signal well preserved. To analyse the results in the strong interference region as highlighted in Figs. 3a and 3b, the zoom-in figures are presented in Figs. 4a and 4b. In the shallow section (black circles), one might carefully observe the signal hidden behind the blending inferences even before the deblending, whereas the region with strong energy overlap (blue boxes), LRDB effectively removed the crosstalk and retrieved the hidden signal which is very weak compared to the noise and events which are also evidenced in nearby stacked crosslines.

Figure 4c shows respectively the normalized amplitude spectra of the data windows before (Fig. 4a) and after (Fig. 4b) the application of the deblending process. The data before deblending is dominated by the strong crosstalk energy that represents the primaries from the subsequent shot. One can clearly identify the receiver notch at round 45Hz. After the application of LRDB, the amplitude spectrum becomes more balanced particularly at low frequencies and its shape similar to what is expected for unblended data at the corresponding time in the section. After the application of LRDB, the receiver notch is no longer visible and there is no apparent de-noise effect (as is often seen with similar technologies (Maraschini et. al, 2016)). As such, we believe the LRDB is robust in the presence of acquisition noise such as swell and can be applied at early stages of the processing.

Conclusions

Deblending using a rank-minimisation formulation is an attractive technique for source separation and reveals information from each individual source. We have shown that using a spatio-temporal domain factorization, LRDB provides practical and stable solutions for triple-source data deblending. The formulation of LRDB is generic and can handle all configurations of simultaneous shooting. Application of LRDB on triple-source towed streamer data shows good results in terms of reducing the crosstalk while preserving the signal and its frequency content. Our future plan is to test this new technology on a variety of simultaneous shooting configurations such as penta-sources and OBN.

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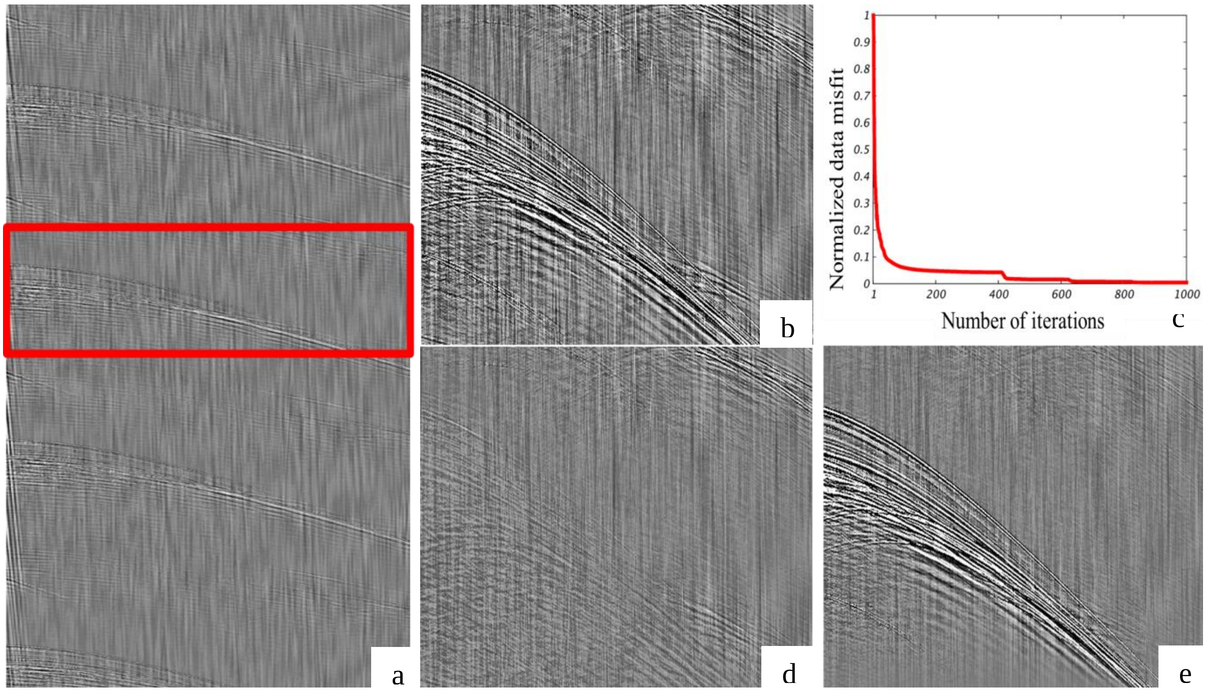

Figure 2 *a: a typical shot for LRDB, b: zoom-in section as highlighted in 2a before LRDB, c: The normalized value of the objective function over the LRDB iterations, d: same section in 2b after LRDB for the first source in 2a, e: same section in 2b after LRDB for second source in 2a.*

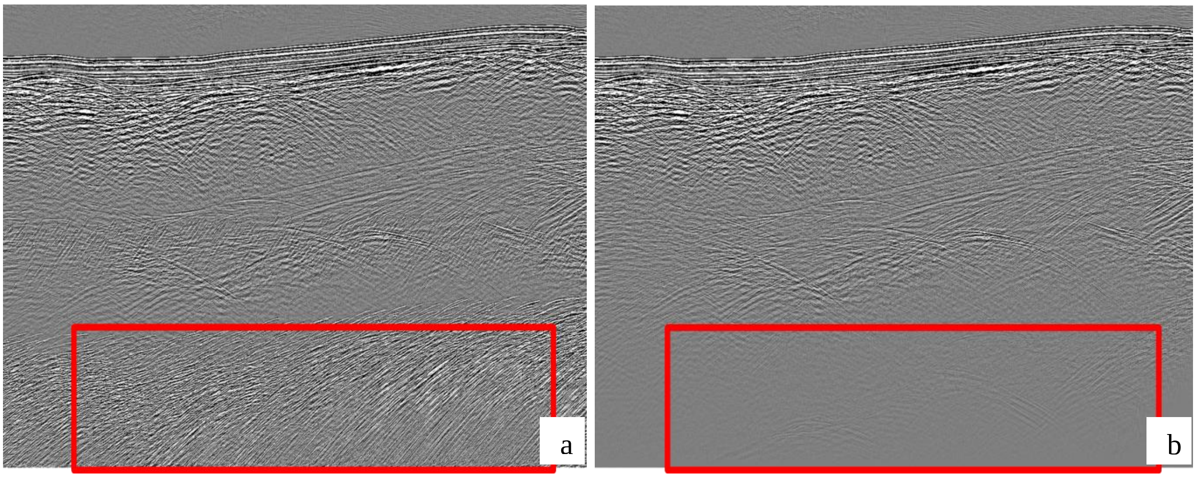

Figure 3 *a: a crossline stack before LRDB, b: same crossline in 3a after LRDB.*

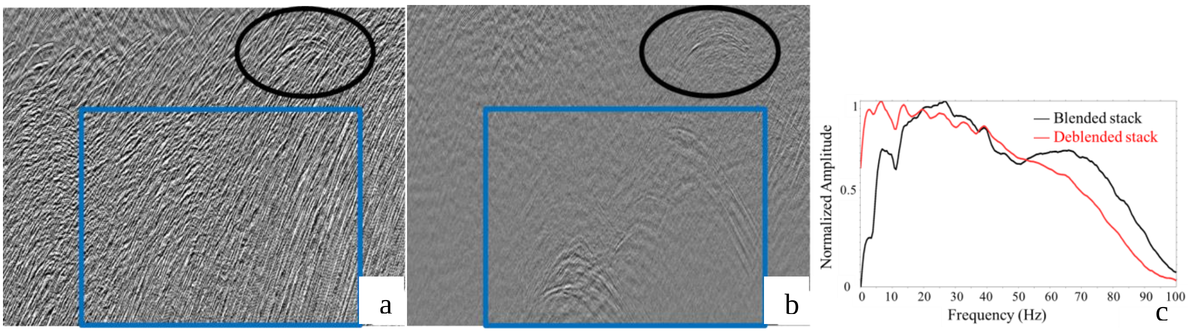

Figure 4 *a: zoom-in section of the highlighted area in Fig. 3a before LRDB, b: zoom-in section (same section as in 4a) as highlighted in Fig. 3b after LRDB, c: the normalized amplitude spectra of the sections in 4a and 4b.*