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Recovery of Blended Data - A Sparse Coding Approach for Seismic Acquisition

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SUMMARY

Simultaneous shooting is one of the main levers to increase the cost-effectiveness of seismic data acquisitions
- either by decreasing the acquisition time or increasing the shot density. It is then fundamental to design efficient source separation solutions to recover blended data. We address the de-blending problematic
in the context of land vibroseismic as its operational models are naturally suited for blended acquisition. In the case of multiple autonomous vibrator trucks, the essential criteria of shooting time randomness is met and at the same time, many constraints encountered with classical acquisition disappear (such as shooting time patterns). Fully unconstrained source acquisitions open the way to unprecedented production rates and shot densities. Simultaneous shooting acquisition can be considered
as a case of Compressed Sensing (timely compressed data). Applying concepts and techniques from this field, we design a deblending procedure based on inverse problems in the Curvelet domain. We use a mathematical formulation to address simultaneous source acquisition. The data recovery is based on the search of the sparse code of the "clean" data in the Curvelet domain, through a l1 regularized inverse problem. Our procedure has been successfully used to deblend 3D common receiver gathers from a real blended acquisition.

Introduction

Recent developments in applied mathematics give us a new selection of powerful tools to address acquisition challenges. The new paradigms promoted by the Compressed Sensing theory provide excellent reasons to acquire seismic data in a compressed manner. As stated in (Candès et al., 2006; Donoho, 2006) two main requirements have to be fulfilled: (i) the sampling scheme needs to be incoherent and (ii) the seismic volumes must be sparsely represented in a specific domain. Seismic data collections are naturally 5-dimensional structures with four spatial dimensions (sources and receivers) and one temporal dimension. Incoherent sampling can be achieved by randomizing along sensing dimensions: spatially by randomizing in the receiver and source positions and/or the shooting times. In this paper we focus on the recovery of data from simultaneous source acquisitions, in particular land vibroseis acquisition which, despite very complex data structure, offers easy ways of randomizing shooting time. We model seismic acquisitions in a mathematical way which enables us to turn the recovery into an inverse problem, (Li et al., 2013; Lin and Herrmann, 2009). We gather the shooting times, positions, and signatures of the shots in one operator, called the operator of measurements. The deblending of continuously recorded data is done by solving inverse problems and this procedure is done one receiver at a time.

Our deblending procedure leverages (i) the fact that seismic volumes can be sparsely approximated in some domain (Curvelet domain) and (ii) the multiple degrees of freedom in land vibroseis acquisitions. Unlike marine acquisition, land vibroseis acquisition offers numerous possibilities for efficiently implementing Compressed Sensing principles, and in particular randomizing of the shooting times. Furthermore the absence of a time shooting pattern as required by the theory renders the operations even more efficient. In the case where each vibrator truck is independent, the shooting orders are triggered by the drivers when the trucks are in the shooting positions. This configuration naturally fulfils the randomness required and releases the operation models from the constraints of more classical acquisition patterns like flip flop, slip sweep, DS^3, etc, (Rozemond, 1996; Bouska, 2009). As the inversions are based on sparsity-promotion in the Curvelet domain which is based on the Fourier domain, the denser the source grid the better. Hence, the method is well-suited for dense acquisitions.

We begin with describing the acquisition and data models, and then use these to solve a classical optimization problem from the field of Compressed Sensing. The procedure is refined by adding a weighted l_1-norm and a final least-square inversion. Finally we illustrate our method using real data from a simultaneous acquisition.

Acquisition and Seismic Data Models

In seismic acquisition, we are interested in the impulse responses (seismic traces) between the receivers and the sources. In vibroseis acquisition, we observe these through a measurement operator. This operator gathers all the information about the acquisition, i.e., source signatures, shooting times and shot positions. Each continuous record from any receiver can be expressed as the multiplication of this operator and the seismic traces,

$$d = \mathrm{O_m}(u) = \mathbf{MR}u \tag{1}$$

where d is the continuous record from a receiver (uncorrelated raw record) and u is a full volume of common receiver impulse responses (seismic traces). The operator $\mathrm{O_m}$ can be decomposed as two matrix operations: one restriction $\mathbf{R}$ and one multiple convolution $\mathbf{M}$, (Li et al., 2013). The restriction maps the full volume u to the acquired seismic traces. In most cases $\mathbf{R}$ is a mask containing 0 and 1 (skipped points), but it can also be an interpolation operator which maps the volume to the exact shot positions. $\mathbf{M}$ is a multiple convolutions operator; for each seismic trace it computes the convolution between the trace and the source signature emitted at that position and then adds it at the shot time. The sum of all these contributions theoretically forms the continuous record d. As the source signatures can be measured during vibroseis acquisition, we use them to build $\mathbf{M}$. Taking into account the fundamental and the harmonics eases the deconvolution process and enables us to remove harmonic corruptions. Figure 1 illustrates the mathematical model. The sketch on the left hand side shows that the continuous raw record d is equal to the sum of all the vibrator contributions. On the right, we show the model written as a matrix product. The matrix has Toeplitz blocks, i.e., small Toeplitz convolution matrices formed by the source signature associated with each shot.

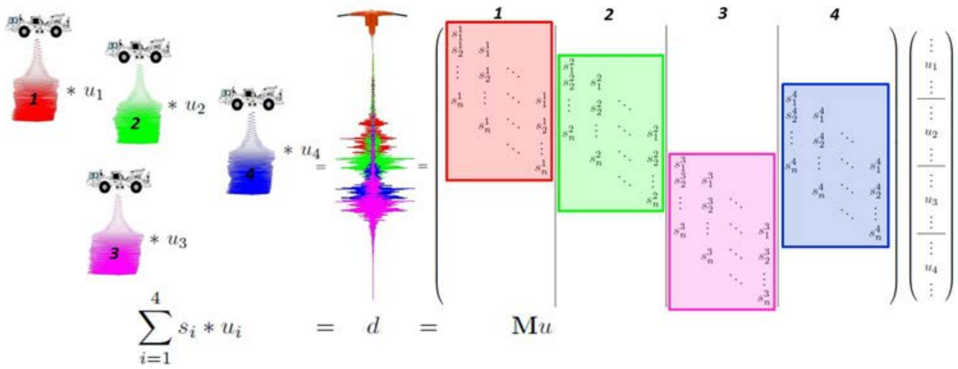

Figure 1 *Sketch and Mathematical Model of a vibroseismic acquisition. Four autonomous vibrator trucks shooting at four different locations, each of them emitting a source signature* s_i*. The continuous raw record d is equal to the sum of the four contributions, each of them being equal to the convolution between the seismic trace* u_i *and the source signature* s_i*.*

In the case of classical acquisition schemes like flip-flop or slip-sweep, the problem in (1) has a unique solution in the emitted bandwidth. The seismic traces are estimated by computing the correlation between d and the reference signal (usually a sweep) i.e., by applying the adjoint operator of $\mathbf{M}$ (containing only the fundamentals) to d. Most of the time, this step is automatically done by the acquisition software and is known as correlation.

In the case of blended acquisition, there is not enough information in the recorded data d to uniquely determine the right common receiver volume. The dimension of d is often much lower than the dimension of $\mathbf{R}u$, in this case the problem is said to be under-determined. The ratio between these two quantities can be used to assess the blending level of the acquisition. Therefore we need to add information about the expected seismic data to solve the problem. Compressed Sensing theory proposes adding information by searching for sparse solutions in certain domains. We use the Curvelet domain to model the seismic volumes (in general, 3D common receiver volume),

$$u = \phi x \tag{2}$$

where ϕ is the backward Curvelet transform and x the vector of coefficients describing the seismic volume u. It has been shown in (Candès and Demanet, 2005) that seismic volumes can be sparsely approximated in the Curvelet domain. This means that we can find x such that (2), with x being sparse i.e., with few non-zero coefficients. By combining the information from the recorded data in (1) and the assumption of sparseness, we succeed in recovering unblended seismic data from blended records.

OPTIMIZATION PROBLEM AND DEBLENDING PROCEDURE

The assumptions made above lead us to write the problem as follows,

$$\arg\min_x \; ||x||_0 \text{ subject to } ||\mathbf{MR}\phi x - d||_2^2 < \sigma \tag{3}$$

where $||.||_0$ is the $l0$ pseudo-norm which is equal to the cardinality of the non-zero coefficient of x and σ represents the noise level on the raw records. Unfortunately the optimization problem in (3) is a combinatorial problem and is not solvable in a reasonable time. As it is often the case, such problems are transposed into convex ones (much easier to solve),

$$\arg\min_x \; \left\{||x||_1 + \lambda||\mathbf{MR}\phi x - d||_2^2\right\} \tag{4}$$

with λ an hyper-parameter used to balance the data-fitting term (least-square) and the sparsifying term (l_1). The above formulation is known to be a good approximation of the non-convex problem in (3). As suggested in (Candès et al., 2008), we introduce some weights on the Curvelet atoms. The weights correspond to additional information on the atoms by discriminating these by position and angular orientation in the volume. For each atom, a weight is computed and then the minimization is done over a weighted l_1-norm instead of a simple l_1-norm as follows,

$$\arg\min_{x} \left\{ ||Wx||_1 + \lambda ||\mathbf{MR}\phi x - d||_2^2 \right\} \quad (5)$$

where W is a diagonal matrix formed by the weights on the Curvelet atoms. Equation (5) can be efficiently solved using classical linear programming algorithms. Under certain conditions and with good parametrization, we obtain a sparse vector representing the unblended seismic data volume in the Curvelet domain, but we often have to handle artefacts and some loss of amplitude. To overcome these imperfections, we finalize our procedure by doing another inversion on the non-zero coefficients of the vector x (usually called adaptation). This step is a classic least-square inversion on a restricted support,

$$\arg\min_{x} ||\mathbf{MR}\phi \mathbf{S}x - d||_2^2 \quad (6)$$

where $\mathbf{S}$ is the restriction operator on the support computed in (5). The solution x_0 of (6) is called the sparse code of the deblended seismic data volume in the Curvelet domain. The model of the "clean" seismic traces is then equal to $\mathbf{R}\phi x_0$. It is often safer to output the difference between the blended traces and the blending noise model computed from $\mathbf{R}\phi x_0$. Indeed, it is hard to be sure that all of the seismic information is contained in the model as the most important events for imagery are often the smallest ones energy-wise.

Examples

Historically, PDO has introduced or used high productivity methods (slip-sweep, DS^3) leading to improvements in both quality and production rates in land vibroseismic acquisitions, (Al-Mahrooqi et al., 2012). Following this trend, a blending acquisition test was jointly conducted by ARGAS and PDO to demonstrate the gains of such an acquisition scheme. This test was acquired employing a fixed continuously recording receiver spread of 1.4 km $\times$ 10 km. A total of 12 autonomous vibrators were operating on a polygon of 2 km $\times$ 10 km, each constrained on separate sectors and shooting on a 12.5 m $\times$ 12.5 m grid. The theoretical signature is the same 9-second up-sweep ranging from 1 Hz to 76 Hz for all the trucks. Figure 2 shows results from a common receiver gather, (a) the blended result (obtained by doing only cross-correlations between the continuous raw data and the theoretical signature), (b) the deblended result, and (c) the difference between (a) and (b). Figure 3 shows results from a shot point gather, (a) the blended result, (b) the deblended result, and (c) the difference between (a) and (b). We can see that the deblending procedure succeeds in removing most of the blending corruption without signal compromise. We estimated, from data on the Figure 3, that the blending corruption is attenuated by more than 30 dB. Hence, remaining noise will be easily handled by classical processing sequences.

Conclusion

By leveraging Compressed Sensing concepts and applying these to blended land vibroseis acquisitions, we show that good deblending results can be achieved on complex data and that land vibroseis is well-suited for time-compressed data acquisition. Two main directions of improvement should be investigated in future works: the addition of geophysical prior information (we add some by using a weighted l_1-norm) and the integration of finer information in the measurement operator to render the seismic volumes sparser, like static and amplitude corrections. With effective deblending procedures and a simplification of its operational models, multiple simultaneous sources in land vibroseismic acquisition should be a standard in the future.

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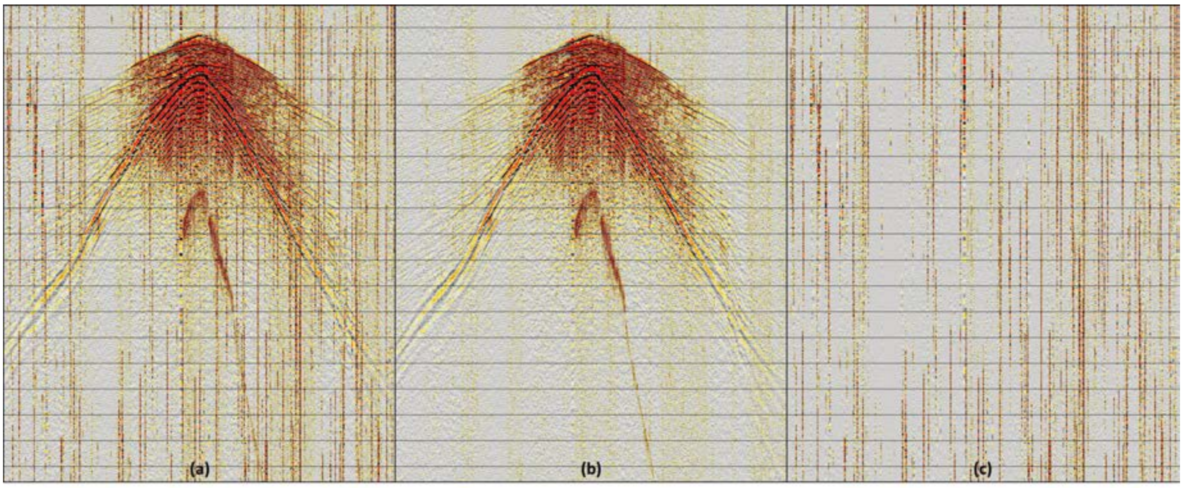

Figure 2 *Deblending results from a simultaneous source land acquisition. A part of a 3D common receiver gather for (a) the blended result (cross-correlation by the theoretical signature), (b) the deblended result, and (c) the difference between (a) and (b).*

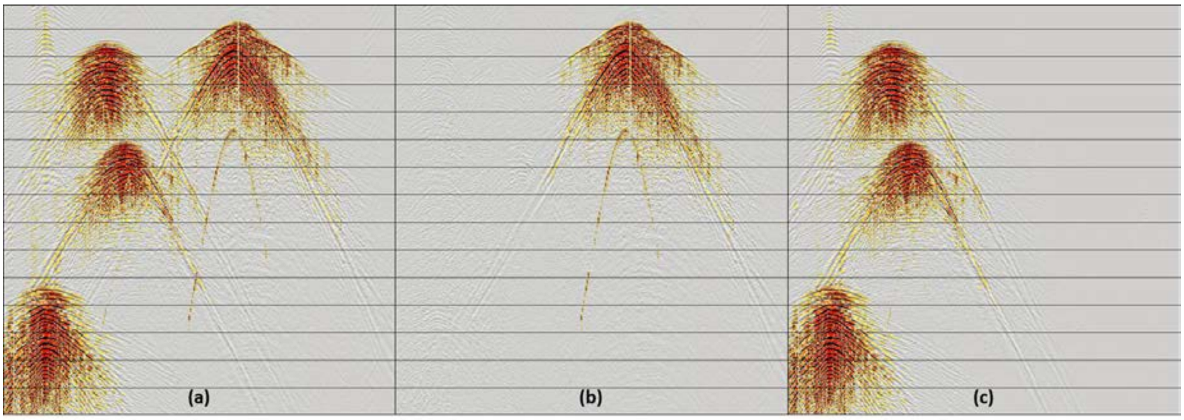

Figure 3 *Deblending results from a simultaneous source land acquisition. A part of a 3D shot point gather for (a) the blended result, (b) the deblended result, and (c) the difference between (a) and (b).*

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