Time-lapse seismic without repetition: reaping the benefits from randomized sampling and joint recovery

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Abstract

In the current paradigm of 4-D seismic, guaranteeing repeatability in acquisition and processing of the baseline and monitor surveys ranks highest amongst the technical challenges one faces in detecting time-lapse signals. By using recent insights from the field of compressive sensing, we show that the condition of survey repeatability can be relaxed as long as we carry out a sparsity-promoting program that exploits shared information between the baseline and monitor surveys. By inverting for the baseline and monitor survey as the common "background", we are able to compute high-fidelity 4-D differences from carefully selected synthetic surveys that have different sets of source/receivers missing. This synthetic example is proof of concept of an exciting new approach to randomized 4-D acquisition where time-lapse signal can be computed as long as the survey details, such as source/receiver locations are known afterwards.

Introduction

Incomplete data, differences in acquisition geometry, differences in salinity and differences in seismic data processing methods can affect the repeatability of the time-lapse or 4-D seismic experiment. Computing weak 4-D differences, is also another challenge, as the overburden becomes more complex (Lumley and Behrens (1998)). Effort is spent on repeating surveys, which can be difficult, depending on the geometry and environmental conditions. We ask the question - is it really necessary to exactly repeat? How will the subsampled data affect the computation of the 4-D signal? In this paper, we will address the fundamental problem of differences in acquisition geometry, where the data is subsampled for both the baseline and monitor surveys.

Seismic data acquired in the field, is usually subsampled, and typically undergoes regularization and interpolation, as part of some standard processing methods – Hennenfent and Herrmann (2008), Kumar et al. (2013), amongst others, have shown interesting applications. In 4-D seismic, processing of time-lapse wavefields, using the similarities between the baseline and monitor data, has been a subject of interest. For instance, Naghizadeh and Innanen (2012) used the projection onto convex sets (POCS) - a Fourier reconstruction and interpolation method, for recovery of the difference section between irregularly sampled baseline and monitor surveys of time-lapse data.

In this paper, we propose an application of the Joint Recovery Method (JRM), introduced by Baron et al. (2005), to the processing of time-lapse data. This method was applied to the recovery of two or more signals by exploiting the fact that the signals to be recovered, share a lot of information, which is typical of the data acquired during the baseline and monitor surveys. To the best of our knowledge, this method has not been applied to any problem in exploration seismology, and in particular, time-lapse data processing. We will apply the method to the reconstruction of time-lapse wave fields which have been acquired with different acquisition geometry. An alternative way of processing the time-lapse data, is to reconstruct the baseline and monitor wave fields independently and we refer to this approach as the Independent Recovery Strategy (IRS). After reconstructing the wavefields using both methods, we will compute the difference section, to reveal the 4-D signal in time and compare their performance relative to each other, and relative to the true or idealized 4-D signal.

Our method relies on the fact that we know the source and receiver locations during the baseline and monitor surveys, but they do not need to be the same or regularly sampled for both surveys. For simplicity, we will apply our method to the recovery of the missing shots in both surveys, although it equally well applies to migrated images and we expect better performance in this case due to the increase in the fold of the data, to improve the SNR. An advantage of using this method is that it saves money, as we do not need to spend valuable time, resources and consequent HSE costs, in the field trying to replicate previous geometry. Our results are shown for a realistic synthetic model and can also be applied to field data examples.

Problem

In a bid to minimize the time and money spent on repeating time-lapse surveys, we propose that the baseline and monitor surveys be acquired without necessarily repeating the source and receiver locations between the surveys. Although, this will yield subsampled baseline and monitor data, it saves time and money. However, since our data is subsampled, we are faced with the task of recovering a densely sampled data - in particular, recovering the missing shots in both data. To solve this problem, we will apply two different methods - IRS and JRM.

Firstly, we model a reference or idealized 4-D signal, which has been estimated from the difference between a densely sampled baseline and monitor survey, with exact repetition of the acquisition geometry. Given a baseline velocity model, an acoustic linearized Born scattering code based on FD, is used to generate densely sampled seismic data. By fluid substitution, a monitor velocity model is simulated, and using exactly the same acquisition parameters for the baseline data simulation, we generate a dense synthetic data from the monitor velocity model. In other words, we exactly repeat the baseline survey, for the monitor survey. The data and 4-D difference section from this simulation, although, is not feasible in the field, will serve as a benchmark to assess the performance of the IRS and JRM, which will be discussed in the next section.

Method

Recall that we are faced with the task of recovering the missing shots in a subsampled baseline and monitor data, which was acquired with different geometries for both surveys. In order to do this, we build on the work by Hennenfent and Herrmann (2008), where the authors have applied the principle of compressed sensing (CS). In summary, CS states that one can recover a fully sampled signal from subsampled measurements of that signal, provided the signal has a sparse representation in some transform domain. Mathematically, given measured data $\mathbf{y} = \mathbf{A}\mathbf{x}$, and defining $\mathbf{A} = \mathbf{RMS^H}$, where $\mathbf{R}$ is a restriction matrix acting on the measurement matrix $\mathbf{M}$, and $\mathbf{S^H}$ is the sparsifying synthesis matrix. In our example, $\mathbf{S}$ is the curvelet transform. The next step is to solve the convex optimization problem

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{y} = \mathbf{A}\mathbf{x} \tag{1}$$

where the recovered wavefield is obtained by $\mathbf{S^H}\tilde{\mathbf{x}}$. In our case, we are designing compressive sampling matrices for sequential source acquisition, which corresponds to $\mathbf{M}$ being the identity matrix, and therefore will be omitted in subsequent representations of the matrix $\mathbf{A}$. For 4-D seismic, we will apply the above formulation and build on the work of Hennenfent and Herrmann (2008), by performing separate reconstruction of the baseline and monitor data (same as IRS stated previously), before computing the difference section. Secondly, we apply the JRM method to the same problem. Now, we have the measured, subsampled baseline data $\mathbf{y}_1 = \mathbf{A}_1\mathbf{x}_1$ and measured, subsampled monitor data $\mathbf{y}_2 = \mathbf{A}_2\mathbf{x}_2$, where $\mathbf{A}_1 = \mathbf{R}_1\mathbf{S^H}$ and $\mathbf{A}_2 = \mathbf{R}_2\mathbf{S^H}$, with $\mathbf{R}_1$ and $\mathbf{R}_2$ different and restricting the acquisition to specific shot locations.

Independent Recovery Strategy

Given $\mathbf{y}_1$ and $\mathbf{y}_2$, and constructing $\mathbf{A}_1$ and $\mathbf{A}_2$, the IRS simply involves solving two sparse recovery problems, independently. That is

$$\tilde{\mathbf{x}}_1 = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{y}_1 = \mathbf{A}_1\mathbf{x} \tag{2}$$

$$\tilde{\mathbf{x}}_2 = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{y}_2 = \mathbf{A}_2\mathbf{x} \tag{3}$$

The calculated 4-D signal, by virtue of linearity, is $\mathbf{S^H}(\tilde{\mathbf{x}}_1 - \tilde{\mathbf{x}}_2)$. This method does not exploit the structure in the problem since the two fully sampled datasets are not independent and share a lot of information. Therefore, the next section describes the JRM, which exploits this shared information.

Joint Recovery Method

The Joint Recovery Method (Baron et al. (2005)), in the context of our problem, exploits the fact that the baseline and monitor wavefields share many significant coefficients in the curvelet domain. Using this background information of the shared coefficients, the problem can be redefined. Let $\mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1$ and $\mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2$, where $\mathbf{z}_0$ is the vector representing the curvelet coefficients common to the baseline and monitor wave fields, whereas $\mathbf{z}_1$ and $\mathbf{z}_2$ are the curvelet coefficients which account for the differences in the wavefields. The corresponding system of equations can be written simply as $\overbrace{\begin{bmatrix}\mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0}\\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2\end{bmatrix}}^{\mathbf{A}} \overbrace{\begin{bmatrix}\mathbf{z}_0\\ \mathbf{z}_1\\ \mathbf{z}_2\end{bmatrix}}^{\mathbf{z}} = \overbrace{\begin{bmatrix}\mathbf{y}_1\\ \mathbf{y}_2\end{bmatrix}}^{\mathbf{y}}$. Solving this system of equations, via convex optimization, yields

$$\tilde{\mathbf{z}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_1 \quad \text{subject to} \quad \mathbf{y} = \mathbf{A}\mathbf{z}. \tag{4}$$

From the solution, we obtain $\tilde{\mathbf{z}} = \begin{bmatrix} \tilde{\mathbf{z}}_0 \\ \tilde{\mathbf{z}}_1 \\ \tilde{\mathbf{z}}_2 \end{bmatrix}$, where $\tilde{\mathbf{x}}_1 = \tilde{\mathbf{z}}_0 + \tilde{\mathbf{z}}_1$, and $\tilde{\mathbf{x}}_2 = \tilde{\mathbf{z}}_0 + \tilde{\mathbf{z}}_2$. The estimated 4-D signal in this case, will be $\mathbf{S}^{\mathrm{H}}(\tilde{\mathbf{z}}_1 - \tilde{\mathbf{z}}_2)$. This result is different from the 4-D signal estimated via IRS, since it does not consider the common curvelet coefficients. The next section discusses the results of applying the IRS and JRM techniques on a synthetic data.

Results

Randomized and subsampled measurements from the densely sampled baseline and monitor data, served as inputs to our proposed methods. We ensured that we make no effort to repeat the same geometry, by randomly selecting independent shots from the idealized monitor and baseline data. We apply the IRS and JRM techniques independently, and recovered the missing shots in the baseline and monitor data. Next, we performed an NMO stack of the recovered data, and computed the difference sections of the stack. We compare the results using both methods, relative to the true (idealized) data. Figure 1 summarizes the result of our numerical experiments. Figure 1(a) is a shot record from the baseline survey. Figure 1(b) is displayed to show the idealized difference between baseline and monitor shot records at the same location. The corresponding results using the IRS and JRM are shown in Figures 1(c) and 1(d), respectively. The complexity of the model we worked with, is more evident in the idealized stacked section, shown in Figure 1(e), while Figure 1(f) is the idealized difference between the stacked sections of the baseline and monitor data. We also compare the 4-D stacked sections obtained using the IRS and JRM, and these are shown in Figures 1(g) and 1(h). These results show that the JRM performs significantly better than the IRS, and it is quite comparable to the idealized data. The SNRs of the stacked difference sections, computed using the IRS and JRM are 16.7dB and 25.2dB respectively.

Conclusions

We have shown a method that helps relax the need for repetition in time-lapse seismic, by exploiting randomized sampling strategies and joint recovery method. Our proposed method - JRM, can be used to obtain high-fidelity 4-D difference sections from time-lapse data volumes which have been sampled randomly and without repetition. The proposed method is efficient, and has been tested on a synthetic time-lapse model. Although, we have only applied this method to time-lapse data which have been acquired with a different geometry, acquisition and processing of the difference section, our method can equally be extended to wave-equation based inversion of the data and this is currently work in progress.

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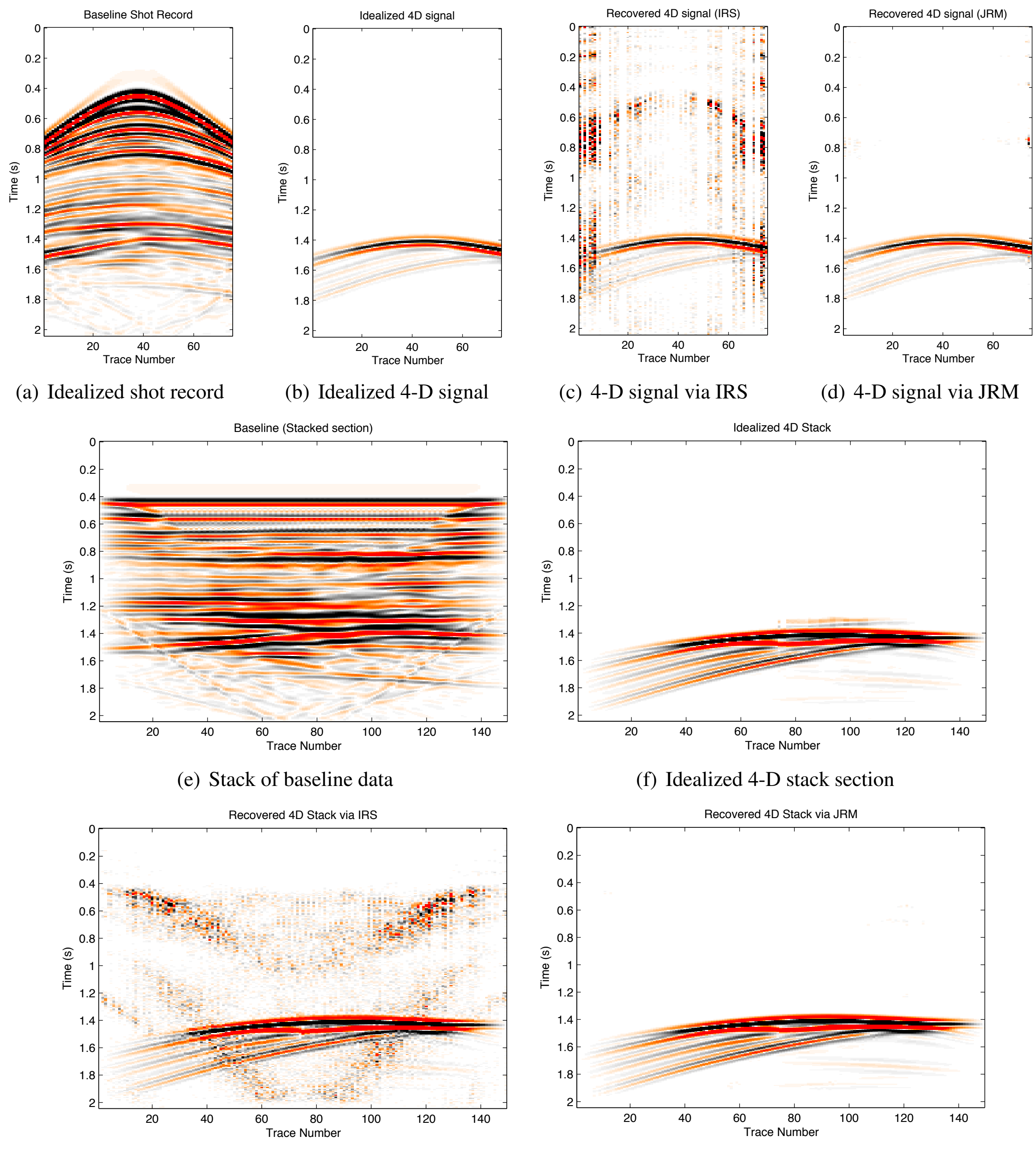

(a) Idealized shot record

(b) Idealized 4-D signal

(c) 4-D signal via IRS

(d) 4-D signal via JRM

(e) Stack of baseline data

(f) Idealized 4-D stack section

(g) 4-D stack section via IRS

(h) 4-D stack section via JRM

Figure 1 *Comparing the Independent Recovery Strategy and Joint Recovery Method for 4-D Seismic*