geoconvention
Calgary • Canada • May 13-17 2019

Time-lapse seismic data processing and inversion using shared information from vintages

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Summary

Time-lapse seismic studies traditionally require replication in baseline and monitor surveys to minimize uncertainty in interpretation of 4D changes. Rather than adhere to this requirement, we present an alternative approach to 4D data analysis that does require survey replication. We show that recovery of high-fidelity vintages and time-lapse difference is achieveable from randomly subsampled time-lapse data that has been acquired from two non-replicated baseline and monitor survey. Our method leverages common information in time-lapse vintages during processing and inversion to extract 4D attributes. We achieve this result by using the fact that different time-lapse data share information and that non-replicated acquisitions can add information when prestack data are recovered jointly using a joint sparsity model from distributed compressive sensing. Finally, we show an application of the proposed model to full-waveform inversion of time-lapse data.

Introduction

Time-lapse (4D) seismic studies involve the acquisition, processing and interpretation of multiple seismic surveys over a period of time. It has been applied for reservoir monitoring and CO_2 sequestration (Lumley, 2001, 2010). To minimize uncertainty in 4D analysis and interpretation, an important but technically challenging requirement is replicability in the time-lapse (baseline and monitor) surveys (Porter-Hirsche and Hirsche, 1998). Various approaches have been proposed to meet this requirement from the acquisition (Eiken et al., 2003; Eggenberger et al., 2014) and processing point of view (Ross et al., 1997; Ross and Altan, 1997; Rickett and Lumley, 2001; Houck, 2007).

To mitigate the requirement to replicate 4D surveys, we present a new approach that has the benefit of reducing cost of time-lapse surveys and does not rely on survey replication (Oghenekohwo et al., 2017; Wason et al., 2017). Our approach derives from the field of distributed compressive sensing (Baron et al., 2009). This new approach addresses 4D acquisition- and processing-related issues by exploiting common information shared by the different time-lapse vintages. To this end, we consider time-lapse acquisition as an inversion problem, which produces finely sampled prestack data from randomly subsampled baseline and monitor measurements. We conclude by adapting the proposed model to full-waveform inversion of time-lapse data and show that our method can minimize uncertainty in interpreting 4D images/models.

Theory

Consider an inverse problem of the form $\mathbf{Fm} = \mathbf{b}$; where $\mathbf{b}$ is observed data; $\mathbf{F}$ is a matrix or an operator depending on the application, and $\mathbf{m}$ is a model to be estimated given $\mathbf{F}$ and $\mathbf{b}$. Furthermore, suppose $\mathbf{x}$ is some representation of the model $\mathbf{m}$ in a transform domain $\mathbf{C}$ such as curvelets (Candes et al., 2006) or Fourier, i.e. $\mathbf{m} = \mathbf{C}^{\mathsf{T}}\mathbf{x}$, T being the transpose. If it is known apriori that $\mathbf{x}$ is sparse or compressible, a solution $\widetilde{\mathbf{m}}$ to the inverse problem (assume $\mathbf{F}$ is linear) can be found by solving the following sparsity-promoting program also known as basis-pursuit (BP)

$$\text{BP}: \widetilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{Ax} = \mathbf{b}; \mathbf{A} = \mathbf{FC}^{\mathsf{T}}; \qquad (1)$$

This inverse problem for model parameters or a signal $\mathbf{x}$ is common in many areas including compressive sensing (CS, Donoho, 2006; Candes and Tao, 2006). Several applications of CS to problems in seismic have also been reported by many authors (Hennenfent and Herrmann, 2008; Herrmann, 2010; Mansour et al., 2012; Wason and Herrmann, 2013), including field data studies (Mosher et al., 2014).

For time-lapse studies, we borrow ideas from the field of distributed compressive sensing (DCS) where a joint sparsity model (JSM-1) that exploits structures in signals was proposed (Baron et al., 2009). The idea is that certain class of signals possess both intra- and inter-correlations that can be exploited during recovery (processing) of the signal. The JSM, which is captured by both equations (2) and (3), models $J \geq 2$ signals such that each of the signals share a common sparse part $\mathbf{z}_0$, and possess sparse "innovations" $\mathbf{z}_j$ for $j \in 1, 2, ..., n$ with respect to this common part that is shared by n processes/experiments. Note that n is also the number of signals in the signal ensemble, which is a collection or group of signals sharing common information.

$$\mathbf{x}_j = \mathbf{z}_0 + \mathbf{z}_j, \qquad j \in 1, 2. \tag{2}$$

This means that for an experiment involving two processes, such as time-lapse seismic acquisition of a baseline and monitor survey, we end up with three unknown vectors.

$$\begin{aligned} \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \end{bmatrix} &= \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2 \end{bmatrix} \begin{bmatrix} \mathbf{z}_0 \\ \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}, \quad \text{or} \\ \mathbf{b} &= \mathbf{A}\mathbf{z}. \end{aligned} \tag{3}$$

In this expression, $\mathbf{A}$, forms a concatenation of matrices linking the observations of the individual experiments to the common component and innovations pertaining to the different processes. As stated previously, the above JSM readily extends to $J > 2$ experiments, yielding a $J \times$ (number of processes$+$ $1)$ system. Rather than solving for each $\mathbf{x}$ independently as in equation (1), the JSM solves for all the $\mathbf{x}$'s simultaneously via the following equation :

$$\text{BP}_{\text{JSM}} : \widetilde{\mathbf{z}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_1 \quad \text{subject to} \quad \mathbf{b} = \mathbf{A}\mathbf{z}. \tag{4}$$

By casting recovery of such signals in this form and imposing a joint sparsity constraint on the solution of equation (4), the JSM gives better signals with high fidelity. To solve equations (1) and (4), we use the software package SPGℓ_1(Van Den Berg and Friedlander, 2008).

In the next section, we present results from application of the JSM to two problems: (i) prestack time-lapse data recovery from data acquired via simultaneous sources (Oghenekohwo et al., 2017; Wason et al., 2017) (ii) full-waveform inversion (FWI) of time-lapse data. The first example pertains to recovery of time-lapse data acquired with simultaneous (time-jittered) sources, a method first proposed by Wason and Herrmann (2013). The second example pertains to applying FWI on time-lapse data using the modified Gauss-Newton (mGN) method proposed by Li et al. (2012). In this case, we incorporated the JSM into mGN as shown by Oghenekohwo et al. (2015).

Example 1

In this example, the observed data is compressed by a factor of 4, thereby reducing the cost of data acquisition. Thereafter, recovery of the conventional prestack data is peformed with/without the JSM. Figure 1 shows the result of this exercise. Figure 1(c) and 1(d) show the observed data obtained from non-replicated acquisition geometries. The time-lapse signal recovered with the JSM, Figure 1(h), is more accurate than the signal recovered without the JSM, Figure 1(f). Finally, we compare the poststack recovered time-lapse signals in Figure 2 that highlights the efficacy of the proposed method.

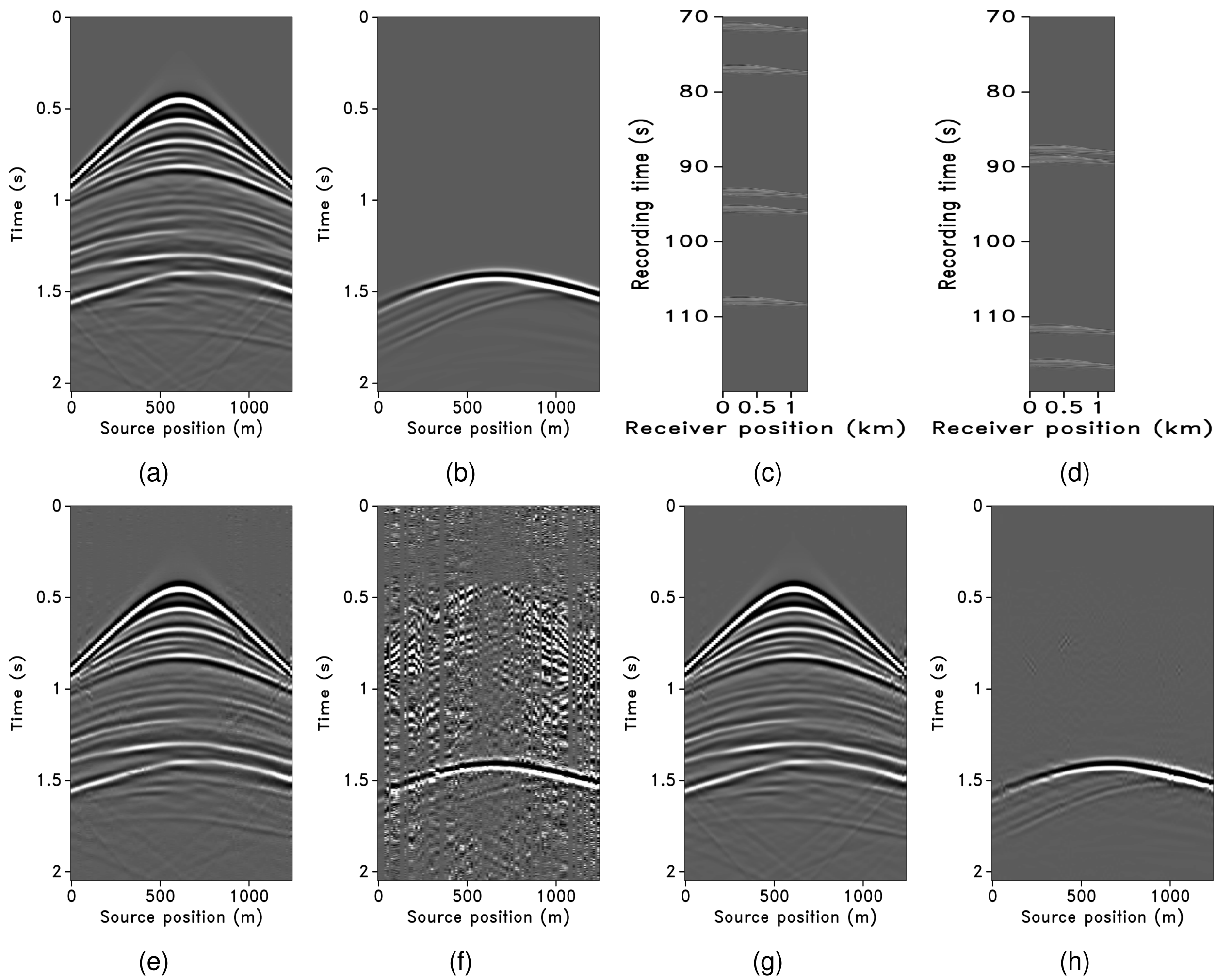


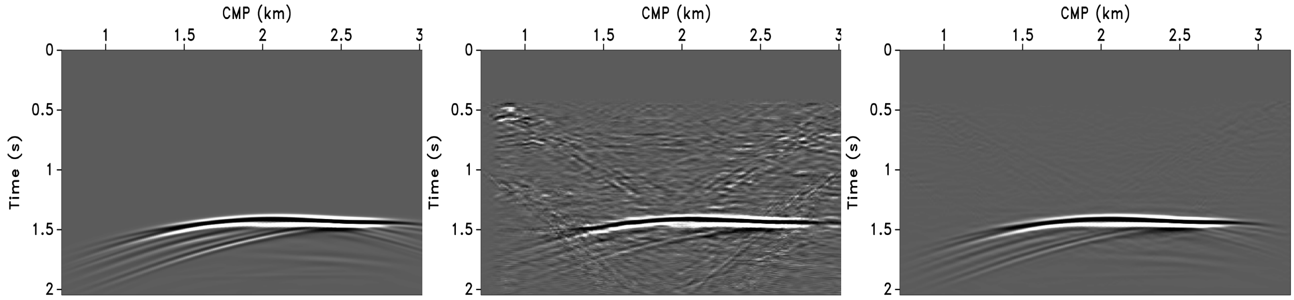
Figure 1: Time-lapse acquisition results. (a) Conventional data (b) True difference. (c) Compressively sampled (sim. src) baseline data (d) Compressively sampled (sim. src) monitor (e) Recovered data w/o JSM (f) Recovered difference w/o JSM (g) Recovered data w/ JSM (h) Recovered difference w/ JSM.

Example 2

The second example involves an application of the JSM to time-lapse FWI. Here, we perform an acoustic frequency-domain inversion for the baseline and monitor velocities. The time-lapse velocity difference is simply obtained by subtracting the inverted monitor from the baseline model. Figure 3(a) shows the true baseline, monitor and difference. Figure 3(b) shows the inversion result without applying JSM, whereby one simply inverts for the baseline and monitor in parallel before subtraction.

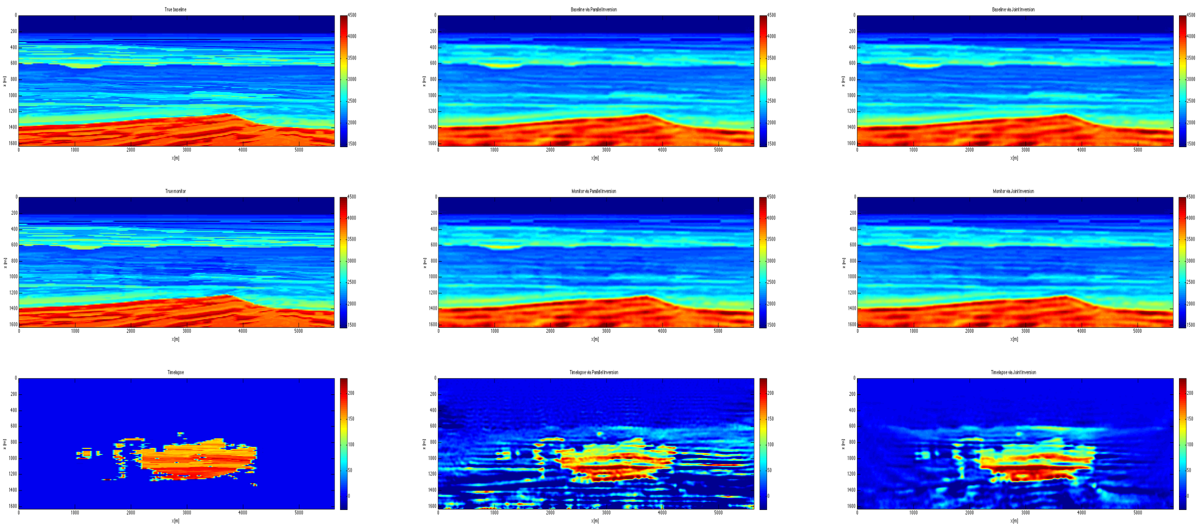
Discussion/Conclusion

Contrary to the prescribed requirement for time-lapse surveys to be replicated, a key feature of the joint sparsity model is that the matrices $\mathbf{A}_1$ and $\mathbf{A}_2$ describing the acquisition geometries in equation (3) do not have to be equal. Another implication of the JSM is that fewer measurements are needed to reconstruct the entire ensemble of signals, which drives down the total acquisition cost. Theoretically, as the number of jointly sparse signals to be recovered increases, only a few data samples need to be collected to ensure accurate recovery. Details of the proof can be found in Baron et al. (2009). Recent application of the JSM to noise atenuation (Tian et al., 2018) and for improving 4D seismic



(a) (b) (c)

Figure 2: Poststack results (a) True time-lapse difference (b) Difference without JSM (c) Difference with JSM.



(a) (b) (c)

Figure 3: Time-lapse FWI Results. (a) True baseline, monitor and difference (b) Inverted baseline, monitor and difference without using the JSM (c)Inverted baseline, monitor and difference with the JSM.

interpretability (Wei et al., 2018) further demonstrate the practical relevance of the model to time-lapse seismic studies.

We have presented a model/method for processing and inversion of time-lapse data that uses information from the vintages. We show that time-lapse data is comprised of a common part and innovations that can be exploited during processing or inversion to produce high-fidelity vintages and time-lapse difference volumes with less uncertainty. A prime conclusion of the proposed method is the opportunity to relax the requirement for time-lapse surveys to be replicated.

Acknowledgements

This is work done at the University of British Columbia and the authors are grateful to the sponsors of the SINBAD project for their support. Felix Oghenekohwo is grateful to the sponsors of Signal Analysis and Imaging Group (SAIG) at the University of Alberta for their continued financial support.

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