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Compressive time-lapse seismic data processing using shared information

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Summary

Time-lapse images void of acquisition and processing artifacts can provide more useful information about subsurface changes compared to those with acquisition footprints and other unwanted anomalies. Although, several pre-processing techniques are being developed and used to mitigate these unwanted artifacts, these operations can be very expensive, challenging and data dependent. Migration, as a processing tool, using a sparsity constraint has been shown to reduce artifacts drastically but little is known about the significance for compressed time-lapse seismic data. Leveraging ideas from distributed compressed sensing, and motivated by our earlier work on recovery of densely sampled time-lapse data from compressively sampled measurements, we present a sparsity-constrained migration for time-lapse data that uses a common component shared by the baseline and monitor data. Our algorithm tested on a synthetic example highlights the advantages of exploiting the common information, compared to ad hoc methods that involve parallel processing of the time-lapse data before differencing.

Introduction

Time-lapse seismic data comprising a baseline and at least one monitor data provides information about subsurface changes over a period of time [Lumley, 2001]. While effort is made to repeat the acquisition geometry or/and processing of the data [Kragh and Christie, 2002], challenges still persist with interpreting the final time-lapse difference. Therefore, it is essential to develop techniques that can improve the results on existing and new time-lapse data. One standard approach in processing time-lapse data is the amplitude differencing analysis where the baseline and monitor data are subtracted to reveal the time-lapse signal, at each processing step. This method can be very delicate especially when there are acquisition or/and processing artifacts in the data. Johnston [2013] gives an excellent review of many of the some of the challenges faced from acquisition to processing of time-lapse data. Commonly referred to as the parallel processing method, this approach does not consider any dependence between the baseline and monitor data. To address the challenges of processing time-lapse data, several joint processing methods have been proposed (e.g. Ayeni et al. [2012]). The main idea in these methods is to use a prior information in the baseline data while processing the monitor data. However, none of these methods have been applied in the context of compressive sensing. In addition, most of these methods rely on the availability of a densely sampled baseline data. In this work, we present a new tool for processing time-lapse data, which uses the shared information in the data sets explicitly as part of an optimization procedure. Leveraging ideas from distributed compressed sensing [Baron et al., 2009], we introduce a joint recovery method that can process time-lapse data from compressively sampled (subsampled) measurements. Application of our method to migration shows significant improvement in the recovered time-lapse signal compared to similar parallel processing technique.

Theory and/or Method

In the rest of the paper, we refer to the time-lapse data as vectors $\mathbf{x}_1$ and $\mathbf{x}_2$. Consider a forward model for processing noise free time-lapse data

$$\mathbf{y}_j = \mathbf{A}_j \mathbf{x}_j \quad \text{for} \quad j = \{1, 2\}. \tag{1}$$

Here, $\mathbf{y}_1$ and $\mathbf{y}_2$ are the observed compressively sampled data. $\mathbf{A}_1$ and $\mathbf{A}_2$ are two operators that define the processing performed on the data. Our objective is to recover good estimates of the true signals, namely the vintages, $\mathbf{x}_1$ and $\mathbf{x}_2$. From the vintages, we can compute the time-lapse signal $\mathbf{x}_1 - \mathbf{x}_2$; by promoting sparsity of $\mathbf{x}_1$ and $\mathbf{x}_2$, we can get estimates of the true signals after solving the following optimization problem

$$\tilde{\mathbf{x}_j} = \arg\min_{\mathbf{x_j}} \|\mathbf{x}_j\|_1 \quad \text{subject to} \quad \mathbf{y}_j = \mathbf{A}_j \mathbf{x}_j, \quad \text{for} \quad j = \{1, 2\}. \tag{2}$$

Solving Equation 2 is exactly the parallel processing method that does not use any prior information from the baseline in the monitor processing. Instead of following independent processing methods, we use ideas from distributed compressed sensing (DCS)[Baron et al., 2009], where we decompose the signals $\mathbf{x}_1$ and $\mathbf{x}_2$ into three different components. Setting $\mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1$, $\mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2$, we introduce a joint processing method termed the joint recovery method (JRM), and solve an optimization problem for estimating the vintages and the time-lapse signal. Using this model, we solve the following problem:

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

where $\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2 \end{bmatrix}, \quad \mathbf{z} = \begin{bmatrix} \mathbf{z}_0 \\ \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}, \quad \text{and} \quad \mathbf{y} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix}.$

By adding the first column in $\mathbf{A}$, we exploit the common information $\mathbf{z}_0$ in the time-lapse data. In the next section we explore the performance of our JRM on migration of time-lapse seismic data and compare the results with a similar migration routine that was performed in parallel, i.e. migration of baseline before migration of monitor. In our example, we use the sparsity-promoting migration technique by Herrmann and Li [2012] because it is fast, reduces migration artifacts and uses ideas based on compressive sensing. Details of this migration algorithm will be omitted here, as it is not the main focus of this work.

Examples

We consider a simple layered time-lapse model with vertical discontinuities. Figure 1a shows the model perturbations for the monitor and the time-lapse difference. The baseline is obtained by adding the monitor to the difference. A finite difference acoustic code is used to generate a densely sampled baseline and monitor data. Our objective is to produce migrated time-lapse images including the difference from the observed data using the same migration algorithm. However, we will compare parallel migration with migration using our joint recovery model. For simplicity, we assume the geometry of the baseline and monitor acquisition is the same and we also assume we have a good background velocity model for migration. The forward modeling parameters for the baseline and monitor data are also the same. So, in this idealized setting, we will process (migrate) the data sets in parallel (independently) and jointly using the JRM. As stated previously, we will adopt the sparsity-promoting migration technique of Herrmann and Li [2012]. The main idea in this migration formulation is to use only a subset of the total acquired data at every iteration step as we update the model perturbation. This dimensionality reduction step has been shown to speed up the migration.

For a fixed number of iterations in the migration, given the observed baseline and monitor data, we observe the final time-lapse migrated images and differences via the parallel and joint methods. Figure 1c and 1d shows the time-lapse results using the parallel method while Figure 1e and 1f shows the time-lapse results using the joint method (JRM). From the results, we notice a significant reduction in the artifacts in the final images using the JRM compared to the parallel method. The efficacy of the JRM is more pronounced when we look at the time-lapse difference from both methods. This improvement using JRM can be attributed to the shared information, which the JRM exploits but the parallel method doesn't.

Conclusions

We have shown a noveau method for processsing time-lapse data that exploits the shared information in the data. Our method shows improved vintages and time-lapse signals after processing compared to ad hoc independent or parallel processing methods. We have also shown how we can apply our method in a migration routine that uses dimensionality reduction and compressive sensing ideas to speed up computations.

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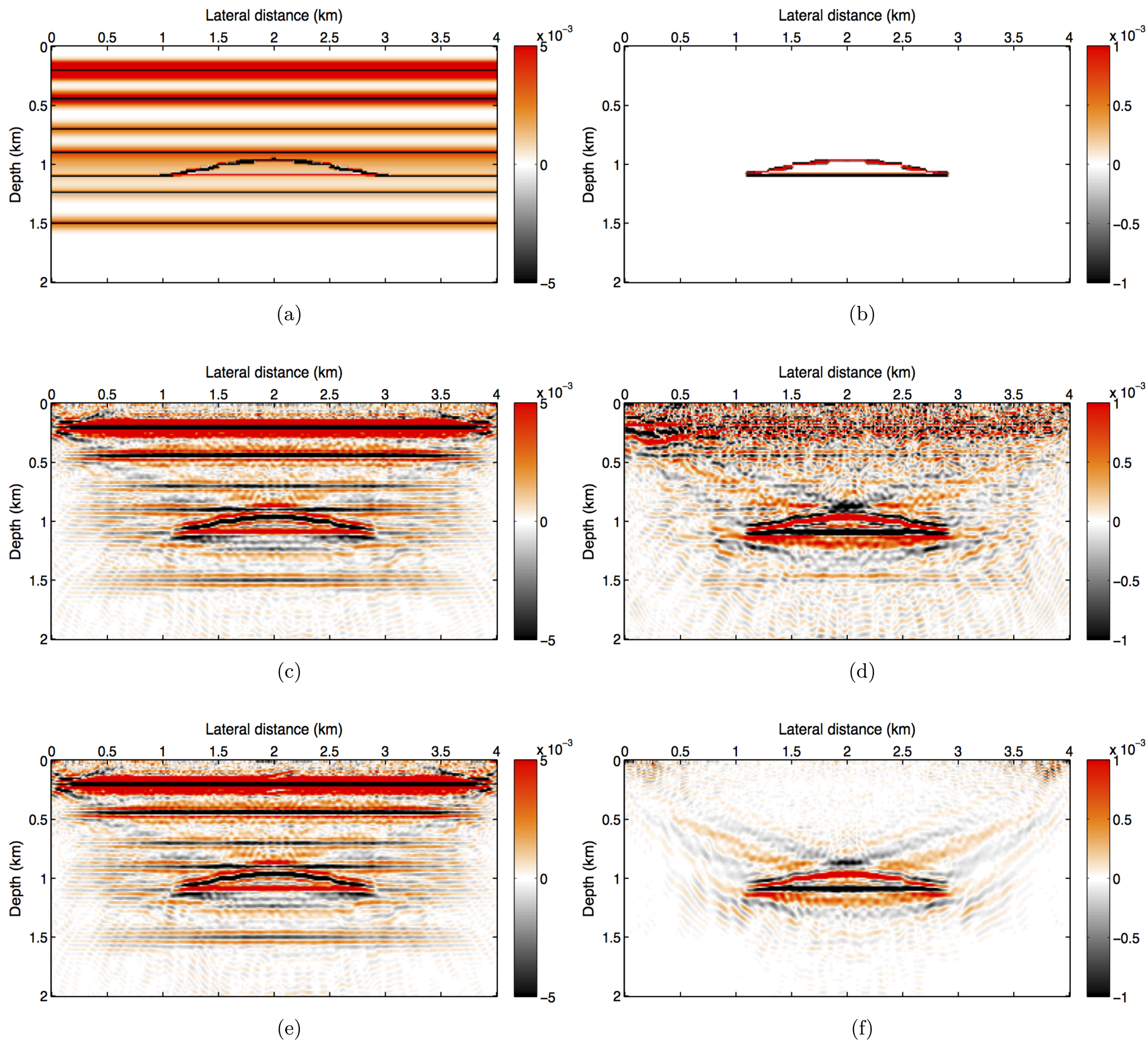

Figure 1: (a) True monitor perturbation (b) True time-lapse difference (c) Monitor image via parallel method (d) Time-lapse difference via parallel method (e) Monitor image via joint method (d) Time-lapse difference via joint method. Notice the attenuation of the artifacts with our joint method compared to the parallel method.