A Data-estimation Based Approach for Quasi-continuous Reservoir Monitoring using Sparse Surface Seismic Data

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Introduction

One of the climate change mitigation options aimed at controlling greenhouse gas contributions from anthropogenic activities is carbon dioxide capture and sequestration (Benson et al., 2005). Monitoring sequestered CO_2 in geologic reservoirs is needed for licensing purposes, reservoir performance assessment, and leak detection. During the injection phase, when the reservoir pressure is forced to change, faults may be reactivated, creating fluid flow conduits. Early detection of leaks through such conduits is most probable if a continuous reservoir monitoring program is in place.

We present a quasi-continuous monitoring strategy for monitoring sequestered CO_2 in geologic reservoirs with surface seismic data. This paper is a further development of the work presented in Arogunmati and Harris (2009). Here, we implement the idea with surface seismic data. We will show how quasi-continuous reservoir monitoring with migrated seismic images differs from quasi-continuous reservoir monitoring with velocity estimation through reflection tomography, highlighting the pros and cons of each.

Figure 1 is an illustration of the approach presented by Arogunmati and Harris (2009). With a conventional time-lapse monitoring approach, large, dense datasets are acquired at each survey. With our approach, only a small subset of the conventional data size is acquired at each incremental survey. Shot-receiver pairs used in each incremental survey vary throughout one complete survey cycle such that the accumulated data acquired at the end of a cycle gives one dense, full survey. The unrecorded data at each incremental survey are estimated and later combined with the sparse recorded data to reconstruct the geophysical image of the subsurface.

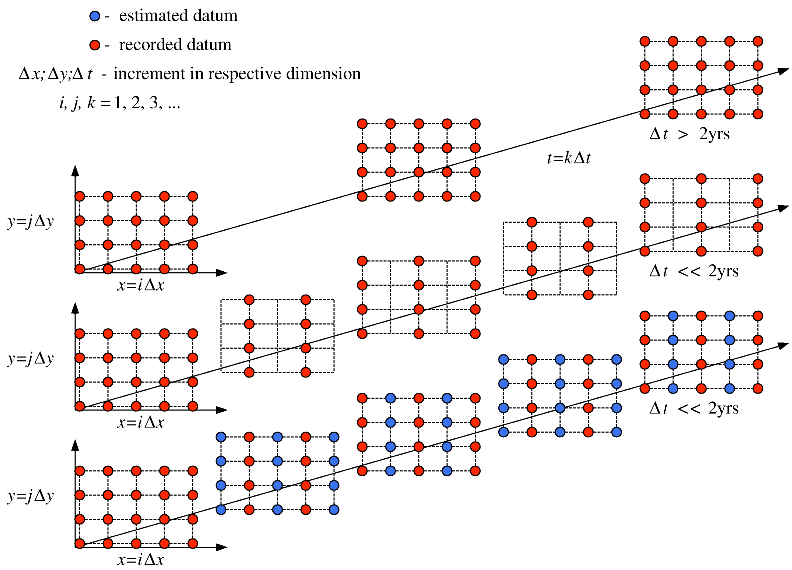

Figure 1 *Illustration comparing the conventional time-lapse approach (top axis) with the proposed approach (middle and bottom axes).*

The strategy shown in Figure 1 is somewhat similar to the strategy used in compressed seismic data acquisition (Candès and Romberg, 2007; Candès and Wakin, 2008) in the sense that partial data are acquired and used in estimating unrecorded data. In a CO_2 sequestration reservoir monitoring project, the object of interest is the injected CO_2 which is expected to flow in a plume-like fashion. What is being monitored is this large-scale, low spatial frequency CO_2 plume and not the finer scale, higher spatial frequency layering within the reservoir.

Theory

We assume that a dataset could be dense (complete) or sparse (incomplete). The sparse dataset is a subset of the dense dataset. With our approach, each incremental dataset acquired is a sparse subset of the dense dataset that could have been acquired at that same time-step. In other words, the dense dataset is the sum of the sparse dataset and an unrecorded dataset. Mathematically,

$$\mathbf{d}_d = \mathbf{S}\mathbf{d}_d + (\mathbf{I} - \mathbf{S})\,\mathbf{d}_d \qquad (1)$$

$$\mathbf{d}_d = \mathbf{d}_s + \mathbf{d}_u \qquad (2)$$

where $\mathbf{S}$ is the data sampling operator, $\mathbf{d}_d$ is the dense dataset, $\mathbf{d}_s$ is the sparse dataset, and $\mathbf{d}_u$ is the unrecorded dataset. Combining (1) and (2),

$$\mathbf{d}_s = \mathbf{S}\mathbf{d}_d \;; \quad \mathbf{d}_u = (\mathbf{I} - \mathbf{S})\,\mathbf{d}_d \qquad (3)$$

Each data vector contains data recorded at all incremental time-steps. The goal is to estimate the unrecorded data, $\mathbf{d}_u$. The fitting goal for estimating $\mathbf{d}_u$ is

$$\mathbf{A}\mathbf{d}_d \approx \mathbf{0} \qquad (4)$$

where the operator, $\mathbf{A}$ is the estimation operator. If we assume the estimated dense data $\tilde{\mathbf{d}}_d$ is approximately the true dense data $\mathbf{d}_d$, equation (4) can be re-written as

$$\mathbf{A}\tilde{\mathbf{d}}_d \approx \mathbf{0} \qquad (5)$$

Combining (2) and (5),

$$\mathbf{A}\mathbf{d}_s + \mathbf{A}\tilde{\mathbf{d}}_u \approx \mathbf{0} \qquad (6)$$

To obtain $\tilde{\mathbf{d}}_u$ from (6), the objective function minimized is

$$\boldsymbol{\Phi} = \left\| \mathbf{A}\tilde{\mathbf{d}}_u + \mathbf{A}\mathbf{d}_s \right\|^2 \qquad (7)$$

In this paper, the prediction error filter (PEF) (Jain, 1989; Claerbout, 1998, 2008) is used as the estimation operator, $\mathbf{A}$.

Synthetic Example

To test our approach, we created a baseline velocity model based on the geology of an oil field off the coast of Norway (Figure 2).

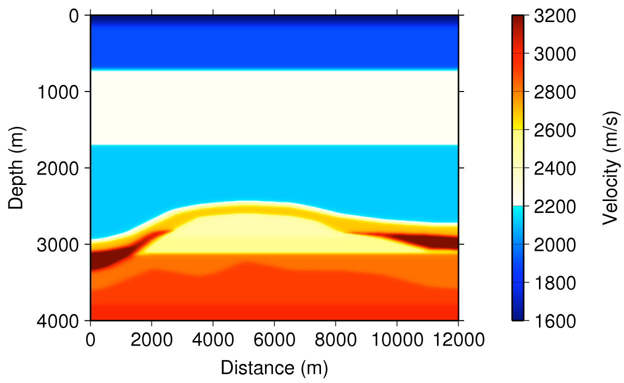

Figure 2 *Baseline velocity model.*

This velocity model was perturbed to produce 20 velocity models representing states of the field after CO_2 injection into the reservoir over a period of twenty months. The maximum change in reservoir velocity subsequent to injection was 3%. Using an elastic wave equation algorithm, we calculated synthetic surface seismic data using shots placed at the water surface and receivers placed at the water bottom. Shot and receiver spacing was made consistent with conventional surveys. Each dataset was then sub-sampled to 10% of its original size to conform to the acquisition strategy described in the introduction section. With this sub-sampling scenario, a complete survey cycle is achieved after ten months. Sample receiver gathers are shown in Figure 3.

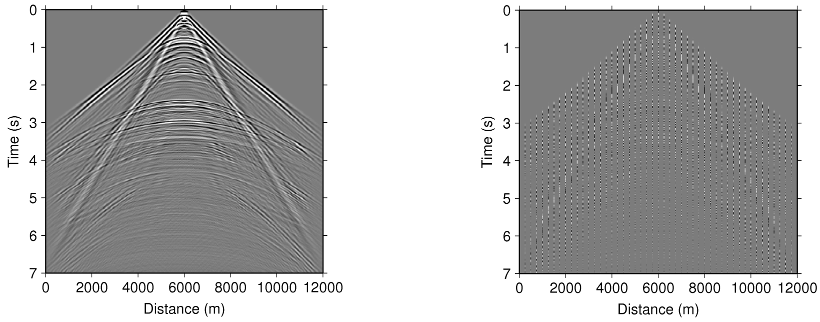

Figure 3 *Sample dense receiver gather (left); and 10%, sub-sampled receiver gather (right).*

We estimated unrecorded data at each incremental time-step using PEFs. Figure 4 shows pre-stack migration results for the true, dense synthetic data; sparse synthetic data; and combined sparse and estimated synthetic data from velocity model number 12 (representing month 12). Selected reflectors are picked on each image. Figure 5 shows the time-lapse image computed from the images shown in Figure 4.

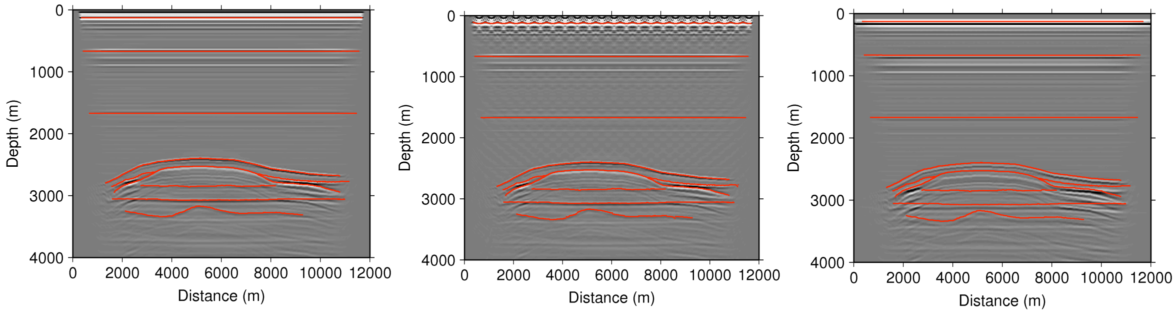

Figure 4 *Pre-stack migrated image from true, dense data (left); sparse data (middle); and combined sparse and estimated data (right). Picked reflectors are marked in red.*

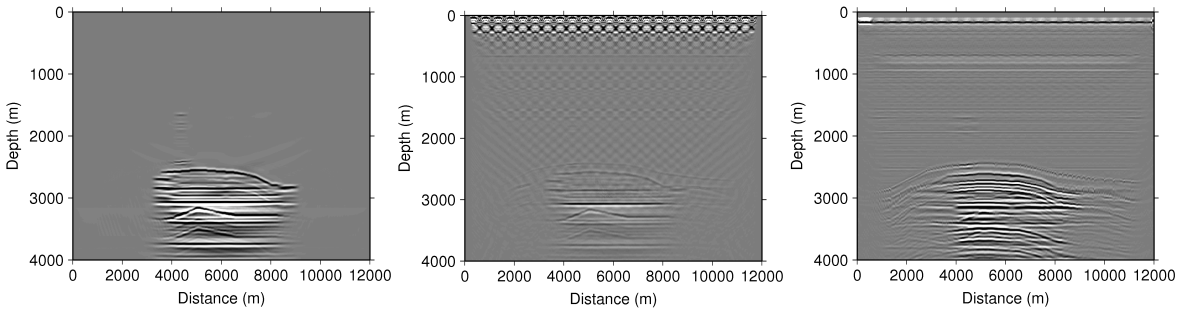

Figure 5 *Time-lapse images from the true, dense data (left); sparse data (middle); and combined sparse and estimated data (right).*

A remarkable observation on Figure 4 is that the reflector picks in the images from the true, and combined sparse and estimated data are identical. The reflector picks on the image from the sparse data show some differences. Figure 5 shows a degradation of the time-lapse images from the sparse data, and the combined sparse and estimated data. The degradation is severe in the image from the sparse data. This is not surprising since only 10% data was used. To obtain more accurate time-lapse images from the combined sparse and estimated data, the data volume constituting the sparse data has to be increased. However, increased data size is not necessarily needed if we are only interested in the reflector depths.

The changes in the reflector depths from one monitor image to another can be used in reflection tomography (Clapp, 2001) to reconstruct the velocity changes with time. These velocity changes can then be used to track the injected CO_2. Figure 6 shows results from reflection tomography using the true, sparse, and combined sparse and estimated data. Even though 10% of the true data was used, the reconstruction with the combined sparse and estimated data is similar to that obtained using 100% true data. However, the reconstruction from the sparse data alone is grossly inaccurate. The inaccuracies originate from the reconstruction errors noticeable in Figure 4.

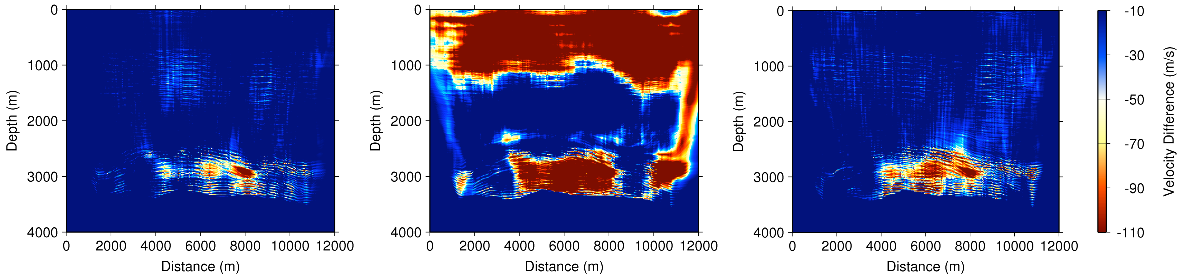

Figure 6 *Reconstructed time-lapse velocity difference models from the true, dense data (left); sparse data (middle); and combined sparse and estimated data (right).*

Conclusions

The quasi-continuous reservoir monitoring strategy presented in this paper is an effective approach for monitoring sequestered CO_2 primarily because it provides an opportunity to detect leaks or other unexpected occurrences soon after they occur. This is particularly useful since an effective CO_2 monitoring program is essential for licensing purposes and monitoring reservoir performance. The strategy involves acquiring sparse incremental data at small time intervals and estimating the unrecorded data at each time interval for use in reconstructing geophysical models. The synthetic example presented here is used to show that data as little as 10% or less of the size of conventional datasets acquired at small time intervals can be used to detect changes in the reflectivity within the reservoir. It can also be used to detect gradual changes in the seismic velocity of reservoirs as CO_2 is injected, using reflection tomography. The size of sparse data needed for good reconstruction varies depending on whether the project goal is to monitor the reservoir with migrated images or with reconstructed velocity models. Future work will involve studying the cost benefits of using the strategy presented in this paper.

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