Time-lapse seismics with randomized sampling

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SUMMARY

In time-lapse or 4D seismics, repeatability of the acquisition is a very crucial step, as we do not want spurious events that are not there. In this paper, we propose an approach which avoids any requirement to repeat the surveys, by using randomized sampling technique which allows us to be more efficient in the acquisition. Our method applies to sampling data using ocean bottom nodes (OBN) as receivers. We test the efficacy of our proposed randomized acquisition geometry for time-lapse survey on two different models. In the first example, model properties does not change with time, while in the second example, model exhibit a time-lapse effect which may be caused by the migration of fluid within the reservoir. We perform two types of randomized sampling - *uniform randomized sampling* and *jittered sampling* to visualize the effects of non-repeatability in time-lapse survey. We observe that *jittered randomized sampling* is a more efficient method compared to *randomized sampling*, due to it's requirement to control the maximum spacing between the receivers. The results are presented, in the image space, as a least-squares migration of the model perturbation and they are shown for a subset of a synthetic model - the Marmousi model.

INTRODUCTION

Time-lapse or 4D seismic data is a set of data acquired at different times over the same area. It can either be two sets of 2D or 3D data. The first survey produces the *baseline* data, while the second survey produces the *monitor* or *repeat* data. The goal of this process is to observe and quantify any time-lapse effect, usually around the reservoir. The time-lapse effect could be caused by migration of the fluid in the reservoir due to steam injection, CO_2 injection, etc.

A major challenge in time-lapse processing is in the repetition of the acquisition for both surveys. Usually, since sampling is never perfect, both the *baseline* and *monitor* survey contain different acquisition imprints, which would lead to spurious signal in 4D. There are many factors that affect the repeatability of time-lapse data, and some of them include offset regularization, spatial regularization, variable fold of coverage, water velocity variations, differences in processing such as multiple attenuation, random noise attenuation, etc. Therefore, effort is being made to repeat the acquition, especially in marine seismic survey.

For time-lapse studies, data is regularly sampled, and as previously mentioned, repeatability of the acquisition , especially in the spatial sampling of the receivers and sources is very significant. For example, in marine seismic survey, by regularly sampling the ocean bottom nodes (OBNs) during the baseline and monitor survey, we fix the receiver locations, which is a step towards repeatability of the acquisition. From the data, changes in subsurface properties is observed by comparing images obtained from the migration and full-waveform inversion (FWI). Some studies have been carried out using conventional time-lapse generated data. Kragh and Christie (2005) studied the impact of repeatability of time-lapse seismic data and the impact on using time-lapse for reservoir characterization. Also, Li et al. (2008) studied purposeless repeated acquisition time-lapse seismic data processing. Recently, Queier and Singh (2012) and Zhang et al. (2013), applied FWI to a time-lapse data for monitoring CO_2 injection and flow.

Compressed Sensing (CS) (Donoho (2006); Candes et al. (2006)), have shown that by randomly (under)sampling data, we can reconstruct the fully sampled data within a certain noise level. There are a few case studies involving the application of this technique to seismic data acquisition. Moldoveanu (2010) applied this technique to seismic data acquisition..

In the same vein, Hennenfent and Herrmann (2008) proposed the *jittered* sampling scheme for seismic data acquisition. This method favours the reconstruction of seismic wavefields with curvelets, because it controls the maximum gap size. Mansour et al. (2012) also showed improved recovery of seismic wavefield by using partial support information. Although, randomized sampling, especially, *jittered* sampling has been successful in reconstruction of seismic wave fields, it's impact on time-lapse seismic data has not been investigated.

In this paper, we will investigate the impact of jittered sampling on time-lapse seismics. To do this, we first propose the methodology by designing the acquisition for the baseline and monitor survey, and then we test the performance of the method on a synthetic model. This is just one example of randomized sampling for seismic data acquisition. Another example is randomized dithered simultaneous source marine acquisition (see Wason and Herrmann (2012)).

METHODOLOGY

Acquisition design

We refer to Hennenfent and Herrmann (2008) and use their *jittered* sampling scheme to design two random realizations or acquisition geometries. The number of receivers is the same in both geometries, however, they differ in the respective positions of the receivers - OBNs in our case. By virtue of reciprocity, we can safely interchange source and receivers. Therefore, a random sampling of the receivers can also be mapped to a random sampling of the source locations. For simplicity, we shall refer to the two randomized jittered gometries as Geom-A1 and Geom-A2. Next, we design two independent acquisition geometries from a discrete uniform random distribution, Geom-B1 and Geom-B2. This mimics an acquisition scheme which does not control the maximum gap size between the receivers. Figure 1 shows the different undersampling schemes. We would compare the results from both sampling schemes to show which method gives better results.

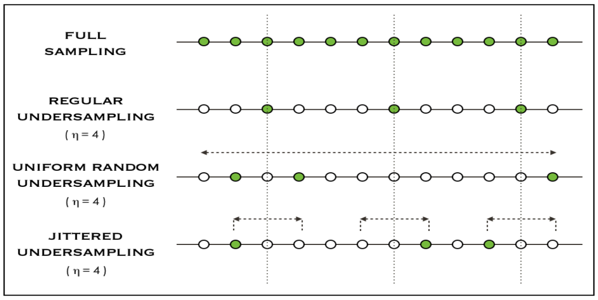
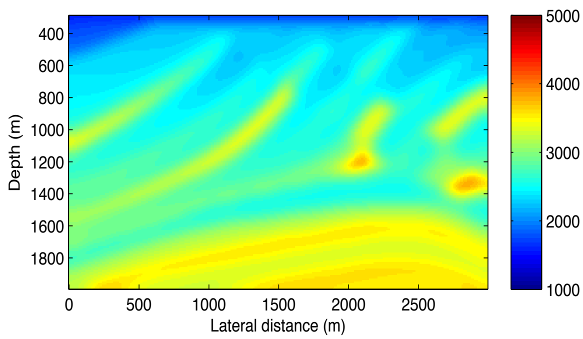


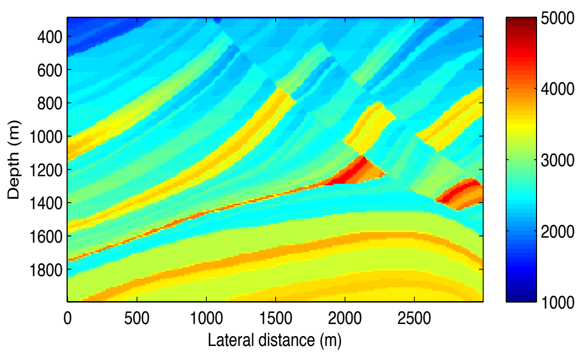
Figure 1: Schematic comparison between different undersampling schemes. η is the undersampling factor. The vertical dashed lines define the regularly undersampled spatial grid.

Modeling

One of the requirements of any seismic imaging algorithm is a good approximation of the background velocity model. In reality, we have no prior knowledge of the velocity model, therefore we use a smoothed version of the baseline velocity model as our backgrund velocity model. The baseline velocity model $\mathbf{m}_b$, which is a subset of the Marmousi model and the associated background model $\mathbf{m}_0$ are shown in Figure 2.



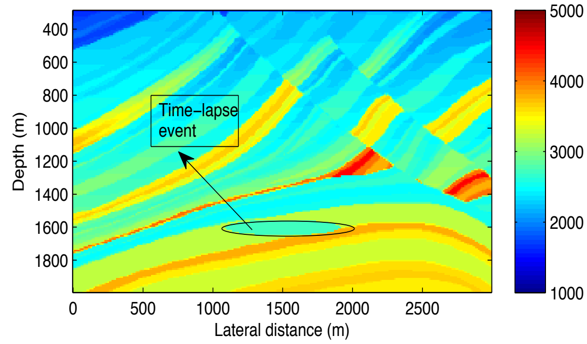
(a)



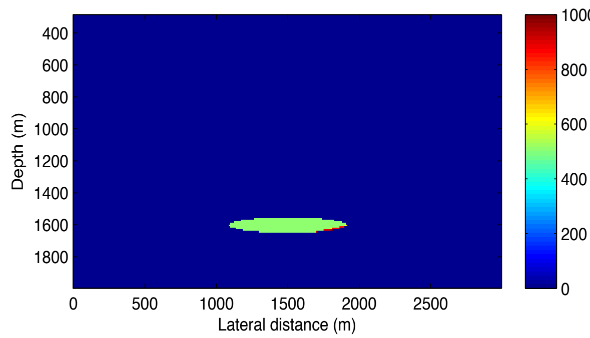
(b)

Figure 2: (a) Background velocity model and (b) Baseline velocity model

The difference, $\mathbf{dm} = \mathbf{m}_b - \mathbf{m}_0$, is refered to as the baseline model perturbation. Keeping the smooth background velocity model constant, we model the monitor velocity model $\mathbf{m}_r$ by adding a time-lapse event $\tau\mathbf{m}$ to the baseline model perturbation and background velocity model, as shown in Figure 3.



(a)



(b)

Figure 3: Monitor velocity model and time-lapse event

Numerical Experiments

Armed with the velocity models $\mathbf{m}_0$, $\mathbf{m}_b$, and $\mathbf{m}_r$, the different acquisition geometries described ipreviously, we generate synthetic seismic data. The model is discretized onto a 300 by 200 grid with 10m spacing. We use 100 equispaced sources at a depth of 50m and 200 receivers (OBNs) at a depth of 300m. The OBNs are randomly sampled according to the geometries, giving rise to the different experiments for the two velocity models. The source wavelet used for the experiments is a Ricker wavelet with a peak frequency of 20Hz and a time delay of 0.2s.

Using our parralel framework for frequency-domain seismic modeling and inversion (van Leeuwen and Herrmann (2012)) , we make linearized data, $\mathbf{d}_b = \mathbf{J}\mathbf{dm}$ for the baseline velocity model. Here, $\mathbf{J}$ is the time-harmonic acoustic Born-scattering matrix linking the observed data $\mathbf{d}_b$ to the perturbations in the medium parameters $\mathbf{dm}$. Note that $\mathbf{d}_b \in \mathbb{C}^{N_f N_r N_s}$, with N_f, N_r, and N_s the number of frequencies, receivers, and sources, while $\mathbf{dm} \in \mathbb{R}^M$, with M the number of grid points. In order to visualize our results, we perform a least-squares migration (see Herrmann and Li (2012) ; Tu and Herrmann (2012)) of the observed data in order to obtain the true-amplitude model perturbation , by solving the following optimization problem.

$$\underset{\delta\mathbf{m}}{\text{minimize}}||\mathbf{d}_b - \mathbf{J}\delta\mathbf{m}||_2^2 \qquad (1)$$

We repeat the same modeling and migration procedure for the monitor velocity model, i.e. $\mathbf{d}_r = \mathbf{J}(\mathbf{dm} + \tau\mathbf{m})$, where we have assumed the background model remains the same. The above migration procedure was done on the entire data set, using 15 iterations of Matlab's lsqr.

In summary, the experiment is in two stages:

- First, we simulate linearized data from the baseline model using Geom-A1 and Geom-A2, and perform the respective inversion described above. We repeat the procedure using Geom-B1 and Geom-B2. This is to assess the effect of randomized sampling on a model which does not portray any time-lapse effect.
- Next, we repeat the experiment on the monitor velocity model, which shows a 4D effect when compared to the baseline model. Here, we simply obtain images of the monitor velocity model using Geom-A2 and Geom-B2.

DISCUSSION OF RESULTS

In our first experiment, we acquired data from the same model using two different random realizations or acquisition geometries. Ideally, If we had repeated the acquisition (i.e. use the same geometry), we should not observe any time-lapse effect in the difference of the respective migrated images. However, our randomized sampling scheme indicates some events in the shallow part of the model as seen in Figure 4. While these events are very distinct in the case of the discrete uniform random acquisition, there is only a tiny fraction of the events in the observed difference for the discrete jittered random acquisition scheme. The efficacy of the jittered case hinges on the maximum gap size allowed between the receivers. Observe that we have only shown the image of the subsurface from a depth of 300m, which is the depth of the OBNs. In our model, the water column is from the depth of 0 to 300m, which is not shown here.

Our second experiment reveals the effect of not repeating the acquisition on a model which clearly shows a time-lapse effect (monitor velocity model). Ideally, the difference between the migrated images of the baseline model and monitor model should distinctly show a time-lapse effect, when the acquistion is repeated. Our experiment with random acquisition geometry is still able to capture this expected time-lapse change as we see in Figure 5. Again, as we observed in the first experiment, we still notice the spurious events in the shallow part of the model but the amplitude of this *false time-lapse* event is less than the amplitude of the *true time-lapse* event.

CONCLUSION

The observed results from our randomized sampling for time-lapse seismics pave the way to make some tentative conclusions. We have used applied a randomized sampling technique (jittered sampling) to time-lapse seismic data acquisition, and we have shown that repeating surveys may not be a necessary criterion for observing any time-lapse changes. As long as we know the locations of the receivers, we do not have to repeat the acquisition. We have applied this on a synthetic model where we assume the OBNs as receivers, are randomly sampled in each time-lapse survey. This can also be applied to a random sampling of the shot locations, by virtue of source-receiver reciprocity. We would also expect our results to improve by using migration medium which promotes sparsity (Li and Herrmann (2012)). The robustness of our method on data with multiples reflection would be a next step to be investigated. Also, it has been applied to a noise-less media. It would be interesting to observe its sensitivity to noise. Finally, the effect of increased subsampling of the data would also be investigated in the near future.

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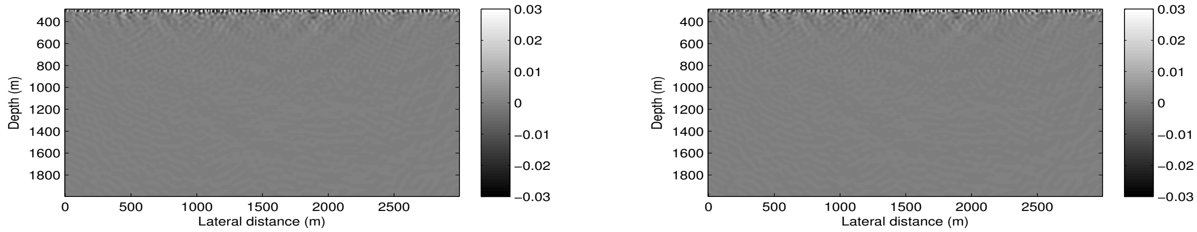
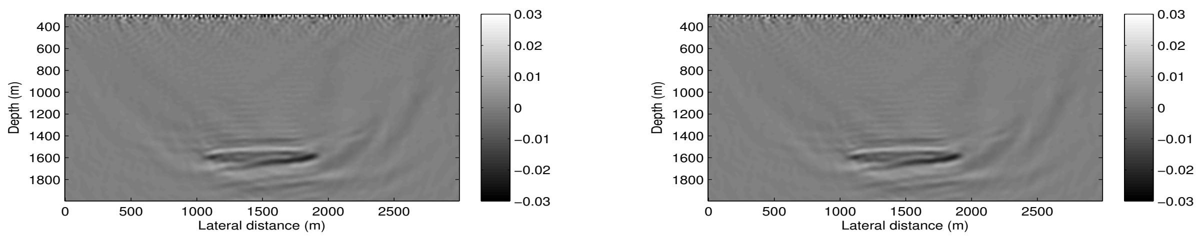


(a) (b)

Figure 4: (a) Difference between images obtained from the baseline using two independent discrete uniform random sampling (b) Difference between images obtained from the baseline using two independent discrete jittered sampling



(a) (b)

Figure 5: (a) Difference between baseline and monitor images using two independent discrete uniform random sampling (b) Difference between baseline and monitor images using two independent discrete jittered sampling

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