Reconstruction of Compressively-Sampled Land Data

Alfaraj, A.; Verschuur, D.J.

DOI
10.3997/2214-4609.202410874

Publication date
2024

Document Version
Final published version

Citation (APA)
Alfaraj, A., & Verschuur, D. J. (2024). *Reconstruction of Compressively-Sampled Land Data*. Paper presented at 85th EAGE Annual Conference & Exhibition 2024, Oslo, Lillestrøm, Norway. https://doi.org/10.3997/2214-4609.202410874

Reconstruction of compressively-sampled land data

A. Alfaraj[1], D.J. Verschuur[2]

[1] Saudi Aramco; [2] Delft University of Technology

Summary

Acquiring economical land data with compressive sensing requires data reconstruction. In the presence of complex near-surface weathering layers, which on their own typically pose a challenge to processing densely sampled data, data reconstruction suffers. The conventional approach of near-surface correction followed by interpolation rely on knowledge of the subsurface. However, obtaining a velocity model is difficult from subsampled data influenced by the weathering layers. To avoid that, we propose to reconstruct the data with a model-independent rank-reduction-based near-surface correction followed by interpolation. We showcase the proposed reconstruction on synthetic data. A field data example will also be presented during the meeting to demonstrate the potential of the method.

Reconstruction of compressively-sampled land data

Introduction

The near-surface weathering layers complicate subsurface imaging and inversion with seismic data (Cox, 1999; Yilmaz, 2001). Subsampling the data for economical reasons, e.g. with compressive sensing (Herrmann et al., 2012), exacerbates the situation as both the near-surface and subsampling reduce the coherency of the data. In this case, data reconstruction becomes essential. There exist many ways to reconstruct the data. Rank-based methods are popular due to their high computational efficiency in processing multidimensional large scale seismic data (Aravkin et al., 2014). However, most existing techniques demonstrate their success in interpolation of statics-free seismic data. In the presence of weathering layers, data reconstruction suffers.

The conventional approach to reconstruct subsampled data affected by the weathering layers is to first perform near-surface correction to improve the coherency of the data, followed by data interpolation (Trad, 2009). These two steps conventionally require pre-hand knowledge of the subsurface model. However, velocity estimation and multiple elimination or distinction between primaries and multiples are challenging from subsampled data, let alone when the data are influenced by complex weathering layers. Moreover, these processes are efforts- and time-consuming.

Recently, Alfaraj et al. (2021, 2023) propose a model-independent low-rank-based near-surface estimation and correction. The method requires no knowledge of the subsurface model. Therefore, it has the potential to bypass the requirements of conventional near-surface correction. However, the method only shows its potential on periodically- and densely-sampled data. When the data are subsampled, the low-rank structure typically associated with densely-sampled date gets destroyed. Similarly, the weathering layers influence the rank structure. They turn the rapidly decaying singular values exhibited by statics-free data into slowly decaying. Therefore, both the weathering layers and randomized subsampling lead to similar influence on the rank structure of the data. In this work, we demonstrate that model-independent low-rank-based near-surface correction followed by rank-minimization interpolation is feasible, but under the following singular values decay conditions.

The singular values decay

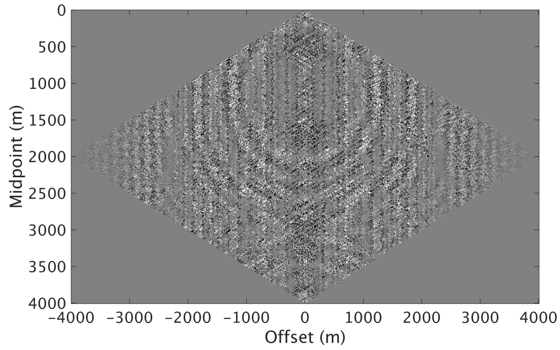
It is known that near-surface correction and randomized subsampling on their own destroy the low-rank structure commonly associated with densely-sampled and statics-free data. When randomly subsampled data are influenced by the weathering layers, the low-rank structure destruction is a result of their combined influence. To use a rank-based approach for both near-surface correction and interpolation, there must exist a hierarchy in the low-rank structure destruction amongst the randomly subsampled data with and without near-surface effects. Such hierarchy enables using a rank-based near-surface correction, which improves the data coherency, and therefore reduce the low-rank structure destruction due to the weathering layers. After that, interpolation becomes possible as only the subsampling effect will remain. To investigate that, we compare the singular values decay of randomly subsampled statics-affected and statics-free data (Figure 1), which shows that the singular values decay of the former is slower than the latter. Also, the singular values decay of randomly subsampled statics-free data is slower than that of densely-sampled data.

Methodology

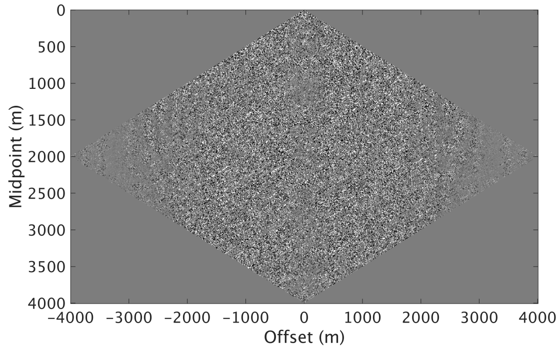
Given the aforementioned singular values decay hierarchy, we propose to reconstruct randomly subsampled data influenced by weathering layers with rank-reduction-based model-independent near-surface correction and interpolation. The former provides data with improved coherency and consequently faster singular values decay similar to that of statics-free randomly subsampled data. That enables data interpolation to a denser grid to obtain matrices of low-rank structure.

Near-surface correction

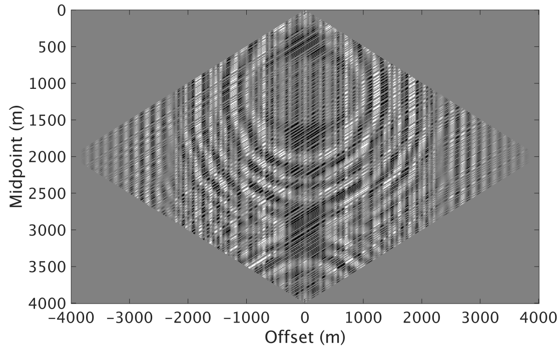
Near-surface correction of rapid variations in weathering layers is generally performed on NMO corrected or migrated data. That is also the current methodology used for near-surface correction of subsampled data, where velocity estimation is more challenging. To avoid the need of a velocity model, Alfaraj et al. (2021, 2023) correct for the weathering effect on regularly and densely sampled data with a



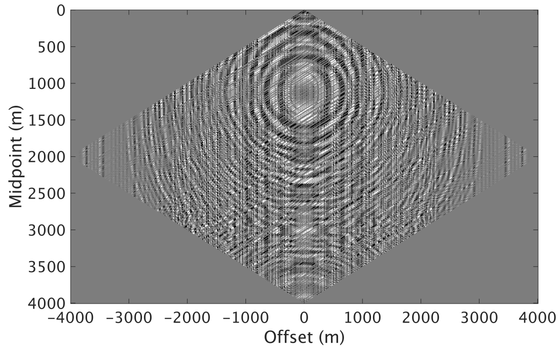
(a) Subsampled data with statics, 18 Hz



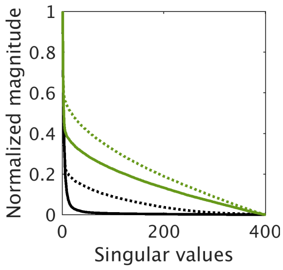
(b) Subsampled data with statics, 49 Hz



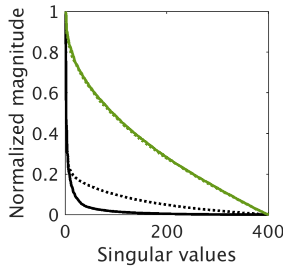
(c) Statics-free subsampled data, 18 Hz



(d) Statics-free subsampled data, 49 Hz



(e) Singular values decay, 18 Hz



(f) Singular values decay, 49 Hz

Figure 1: (a, c) 18 and (b, d) 49 Hz frequency slices in the midpoint-offset domain after removing 50% of the shots at random of data (a, b) affected by ±52 ms of non-surface-consistent statics and (c, d) statics-free data. Plots of the corresponding singular values decay at (e) 18 and (f) 49 Hz, where solid curves represent densely-sampled data and dotted curves represent subsampled data. Black and green colours correspond to statics-free data and data withs statics. At high frequencies, statics have the major influence on the low-rank structure destruction compared to data subsampling.

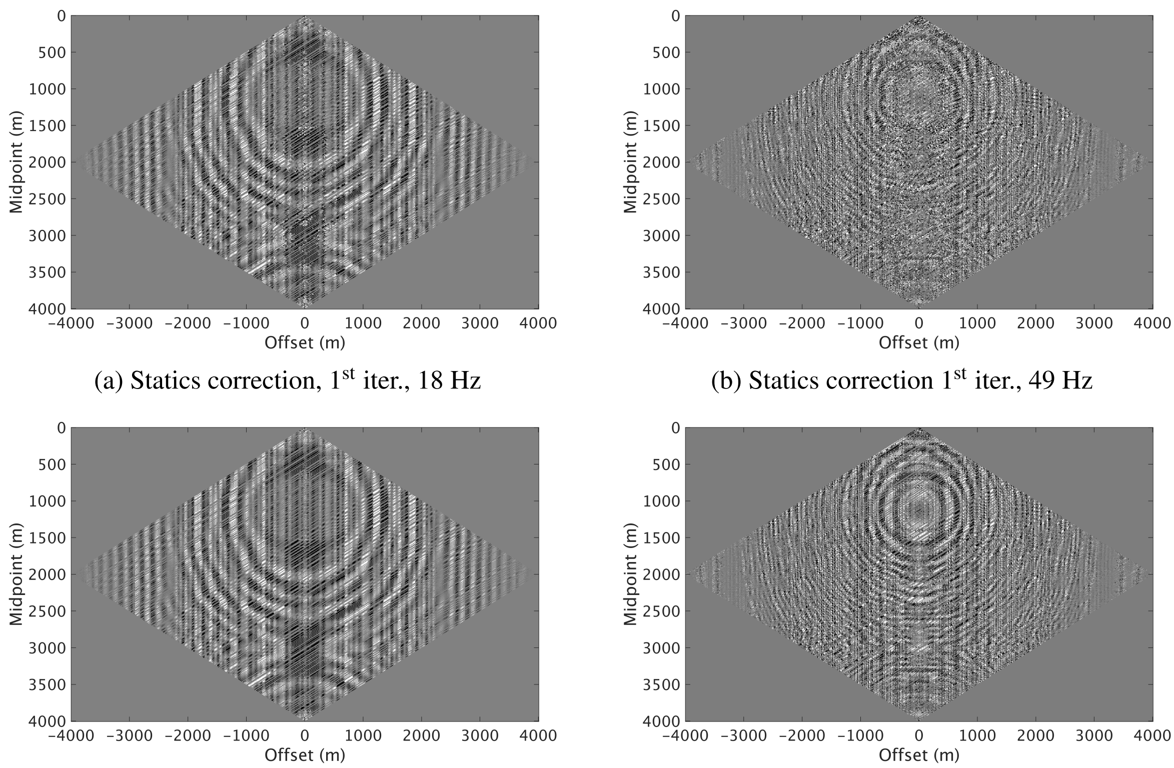
model-independent rank-based approach. Given the singular values decay hierarchy demonstrated in the previous section, we can also utilize the same methodology for randomly subsampled data. Algorithm 1 summarizes the essential steps of the method. It relies on the midpoint-offset domain to create favorable rank structure (step 1), low-rank approximation of frequencies slices (step 6) and statics estimation by cross-correlation of low-rank approximated data $\mathbf{D}_{\mathrm{lr}}$ with the input data (step 9). To extract multi-scale statics and to improve low-rank approximation of high frequencies, the method uses an iterative approach over multiple rank-scales (step 3), and multiple frequency bands (step 7).

Figure 2 shows the results after near-surface correction of the subsampled data displayed in Figures 1a and 1b. We clearly notice the improvement at both low and high frequencies after applying three iterations of algorithm 1. At low frequencies, only one iterations is sufficient to correct for the majority of the statics, as low frequencies are not highly influenced by the weathering layers. In contrast, the high frequencies are more influenced by the weathering layers (compare Figures 1a and 1b), which are the main contributors to the low-rank structure destruction compared to the low-frequencies (compare Figures 1e and 1f). Therefore, the high frequencies require three near-surface correction iterations to improve the data. Given that the data now exhibit improved coherency, we can proceed with data interpolation.

Algorithm 1: Model-independent near-surface correction of subsampled data

Input: Subsampled data, frequency bands and ranks for each frequency slice
Output: Subsampled data after near-surface correction

```
D_mh      Organize the input data in the midpoint-offset domain
~D_mh     Fourier transformation from the time to frequency domain
for loop over rank-scales do
    for loop over frequencies do
        Compute the SVD
        ~D_lr ← Low-rank approximation
        if the desired frequency band for statics-estimation is reached then
            D_lr ← Inverse Fourier transformation of ~D_lr
            Select maximum lag after crosscorrelation of D_mh and D_lr to estimate the statics
            D_mh ← statics correction of D_mh
            ~D_mh ← Fourier transformation of D_mh
D_sr      Organize the statics-corrected data to the source-receiver domain
```



(a) Statics correction, 1st iter., 18 Hz (b) Statics correction 1st iter., 49 Hz

(c) Statics correction, 3rd iter., 18 Hz (d) Statics correction, 3rd iter., 49 Hz

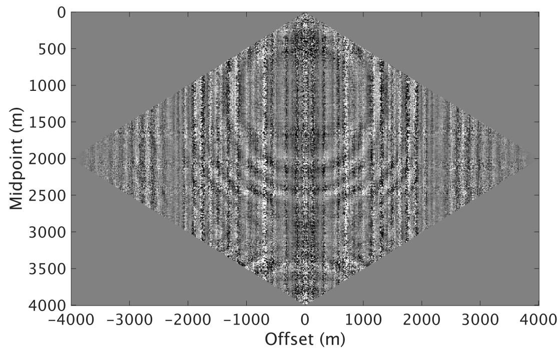
Figure 2: Near-surface correction of subsampled data at the (a, b) first and (c, d) third iterations.

Interpolation

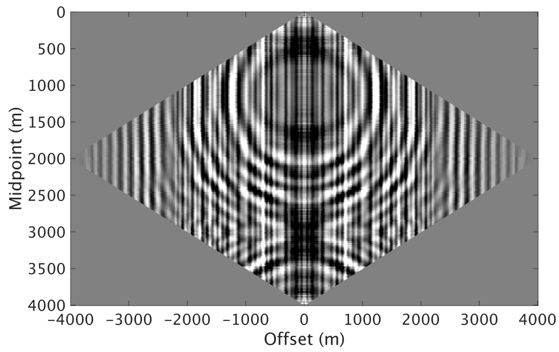
Rank-minimization interpolation is a computationally efficient approach to process multi-dimensional large scale seismic data. The method requires no data windowing as it uses the midpoint-offset domain, which also increases the computationally efficiency. Given a randomly subsampled frequency slice in the source-receiver domain organized as a vector $\mathbf{b}$, we can obtain a densely sampled midpoint-offset frequency slice $\mathbf{X}$ by solving the following rank minimization optimization problem:

$$\underset{\mathbf{X}}{\text{minimize}} \quad \|\mathbf{X}\|_* \quad \text{subject to} \quad \|\mathscr{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \varepsilon, \tag{1}$$

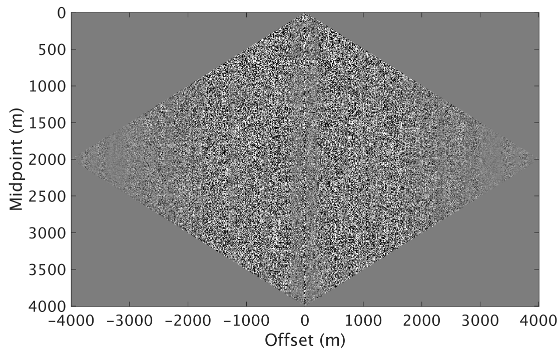
where the operator $\mathscr{A}$ is the sampling-transform operator composed of the adjoint of the midpoint-offset transform domain operator and a measurement operator that removes the unmeasured samples. $\|\mathbf{X}\|_*$ is the nuclear norm and ε is the noise-level. Interpolation of frequency slices without prior near-surface correction leads to noisy reconstruction (Figures 3a and 3c). In contrast, interpolation after near-surface correction with algorithm 1 provides accurate noise-free reconstruction (Figures 3d and 3d).



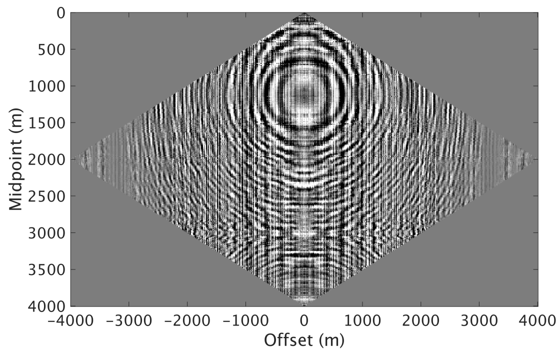
(a) Interpolation without statics correction, 18 Hz



(b) Interpolation after statics correction, 18 Hz



(c) Interpolation without statics correction, 49 Hz



(d) Interpolation after statics correction, 49 Hz

Figure 3: (a, c) Interpolation of randomly subsampled data with statics (Figures 1a and 1b) and (b, d) interpolation of near-surface-corrected data (Figures 2c and 2d) at (a, b) 18 and (c, d) 49 Hz.

Conclusions

Interpolation of subsampled data influenced by the weathering layers require near-surface correction followed by data interpolation. However, these steps rely on knowledge of the subsurface model that is challenging to obtain from such data. To avoid that, we propose to use a model-independent rank-reduction-based near-surface correction and interpolation. We demonstrate that we can accurately reconstruct randomly subsampled data influenced by statics without the need of a velocity model.

References

Alfaraj, A.M., Verschuur, D.J. and Herrmann, F.J. [2023] Low-rank-based residual statics estimation and correction. *GEOPHYSICS*, **88**(3), V215–V231.

Alfaraj, A.M., Verschuur, E. and Herrmann, F.J. [2021] Residual statics correction without NMO – A rank-based approach. In: *First International Meeting for Applied Geoscience & Energy Expanded Abstracts*, 2565–2569.

Aravkin, A.Y., Kumar, R., Mansour, H., Recht, B. and Herrmann, F.J. [2014] Fast methods for denoising matrix completion formulations, with applications to robust seismic data interpolation. *SIAM Journal on Scientific Computing*, **36**(5), S237–S266.

Cox, M. [1999] *Static corrections for seismic reflection surveys*. Society of Exploration Geophysicists.

Herrmann, F.J., Friedlander, M.P. and Yilmaz, O. [2012] Fighting the curse of dimensionality: compressive sensing in exploration seismology. *Signal Processing Magazine, IEEE*, **29**(3), 88–100.

Trad, D. [2009] Five-dimensional interpolation: Recovering from acquisition constraints. *Geophysics*, **74**(6), V123–V132.

Yilmaz, O. [2001] *Seismic Data Analysis*. Society of Exploration Geophysicists.