We N114 03

Two-Phase Automatic Static Correction Algorithm

Y. Sun* (EXPEC ARC GRC Delft, Aramco Overseas Company B.V.), T. Tonellot (EXPEC ARC, Saudi Aramco), B. Kamel (EXPEC, EOD, GDPD, Saudi Aramco) & A. Bakulin (EXPEC ARC, Saudi Aramco)

SUMMARY

Static correction is an effective common approach to correct seismic data for near-surface velocity variations, but to a large extent a robust automatic static correction algorithm is still lacking. We hereby propose a robust two-phase automatic static correction algorithm. First, low-frequency components of the data are analyzed using an advanced genetic algorithm (GA) to estimate both seed statics and time structure, and then the full-band dataset is corrected via back and forth coordinate descent method, with the seed statics as initial values and the time structure as guidance for expected alignment. We demonstrate this new algorithm on a challenging synthetic dataset and then on a field 3D OBC PS dataset focussing on converted-wave statics.

Introduction

The seismic method on land is often used under the assumption of smoothly varying material properties in the lateral direction in the subsurface, but unfortunately this is not always valid in reality. The physical characteristics of the near surface onshore can vary greatly due to the presence of heterogeneities such as topography, wadis, sand dunes, karsts and so on (Keho *et al.*, 2012). Under these circumstances, the assumption of a smoothly varying medium breaks down and strong wavefield distortions appear. This well-known near-surface problem has been recognized since the early days of seismic exploration.

Static correction is a popular tool to handle the near-surface problem (Cox *et al.*, 1999). This method is based upon the assumption that the ray-path through a near-surface layer is vertical so that it only imposes a static time shift on each seismic trace. Some automatic static correction algorithms have been proposed (Rothman, 1986; Vasudevan *et al.*, 1991), which are mainly based upon heuristic algorithms alone.

Previously we have proposed an automatic S-wave static correction algorithm (Sun *et al.*, 2014a), and here we further generalized it to be a novel two-phase robust static correction algorithm. During the first phase, low-frequency components of the data are analyzed using an advanced genetic algorithm (GA) (Sun *et al.*, 2014b), to estimate both seed statics and time structure. During the second phase, the original full-band data is optimized via back and forth coordinate descent (BFCD) method with the seed statics as initial values and the time structure as guidance for expected alignment. One challenging synthetic dataset and one field 3D PS dataset will be used to demonstrate our algorithm.

Two-Phase Automatic Static Correction Algorithm

The workflow of our algorithm is shown in Figure 1. Similar to some published static correction algorithms, our approach also aims at maximizing the stacking power in the final image (Rothman, 1986; Sun *et al.*, 2014a). Phase 1 consists of three steps. The first step comprises extraction of low-frequency components of the data (up to 10 Hz). Next, the low-frequency components are aligned by optimizing the local coherence using the GA, and the statics thus obtained are named “seed statics.” Finally the corresponding time structure is determined from the aligned low-frequency stack image. In Phase 2, the original full-band data is further aligned by the BFCD method (Nocedal *et al.*, 1999), using the seed statics as initial values and the time structure as alignment guidance. Our algorithm can avoid intensive user input, and the whole workflow can be finished in a completely automated manner. Certain fine-tuning of a few key parameters, such as the upper frequency limit and time structure determination window size, can be accomplished by making multiple runs of the algorithm.

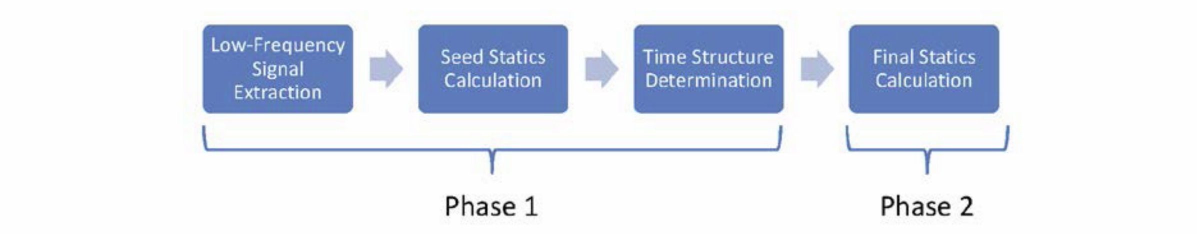

Figure 1 *The workflow of the proposed two-phase automatic static correction algorithm.*

Synthetic Example

We first use a synthetic model, shown in Figure 2, to demonstrate our algorithm. In this synthetic model, a constant density (1,000 kg/m^3) was used, and only primaries were generated. A total of 200 independent receivers were along the receiver cable. An area of 3000 CDPs were modelled comprising 3 inlines and 1,000 crosslines. For this synthetic dataset all CDPs have the same fold of 10. The source is a Ricker wavelet with the central frequency of 30 Hz. With perfect NMO correction, the ideal CDP stack image is shown in Figure 2. To simulate near-surface effects, and also with no loss of generality, we contaminated the data with random static time shifts varying between -/+100 ms for receiver positions only, and later we used our algorithm to recover them. In addition, Gaussian noise was also added to the dataset with an average SNR of 10. The CDP stack section of the synthetic dataset with random receiver statics and noise is shown in the left side of Figure 3, while the corresponding low-frequency CDP stack image is shown in the right side.

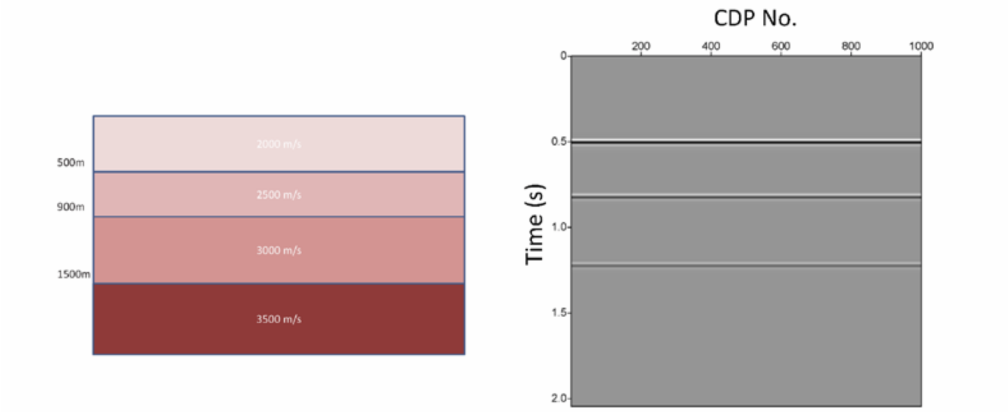

Figure 2 *(Left) 1D synthetic model with four layers and the constant density (1,000 kg/m^3). (Right) Perfect CDP stack image with primaries only.*

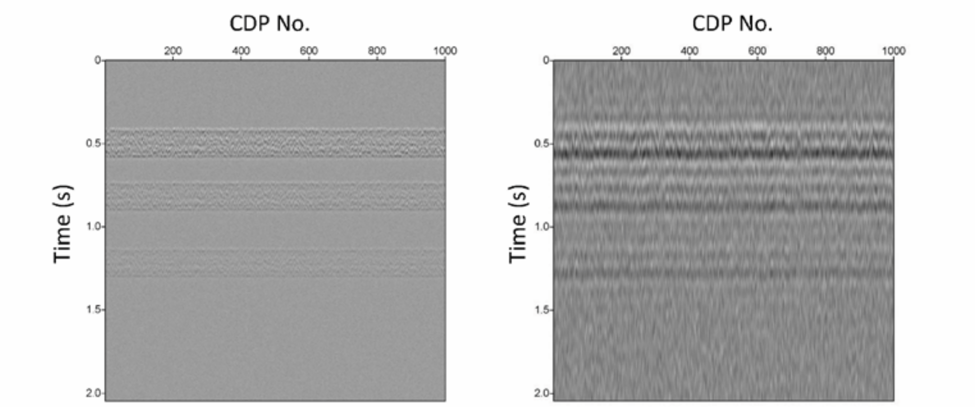

Figure 3 *(Left) CDP stack image of the dataset with noise and random statics introduced. (Right) CDP stack image of the low-frequency components from the raw data (up to 10 Hz).*

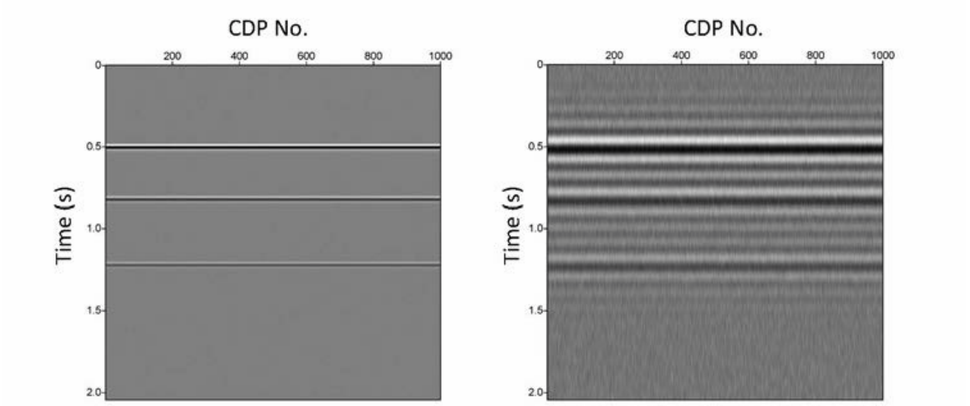

Figure 4 *(Left) CDP stack image of the full-band dataset after applying the two-phase automatic static correction algorithm. (Right) CDP stack image of the low-frequency components after the first phase of the algorithm.*

After phase 1 the seed statics were applied to the low-frequency components, and the corresponding CDP stack showed very good alignment of the reflectors (right side of Figure 4). The final statics were then applied to the full-band data, and final aligned CDP stack is shown in the left side of Figure

4. Please note that even with the presence of noise and very challenging receiver statics, our algorithm still produced a perfect final stack compared to that shown in Figure 2. Figure 5 shows excellent agreement between the random statics applied and the final statics estimated by our algorithm. This proves the robustness and effectiveness of our algorithm.

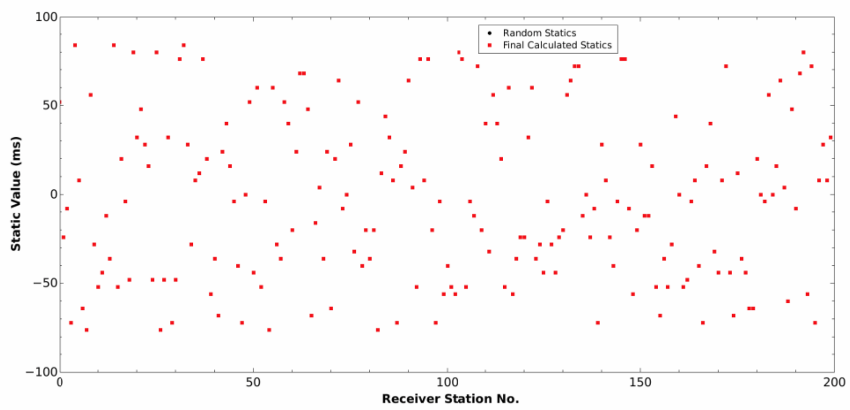

Figure 5 *Comparison between random statics applied and final statics estimated by our algorithm.*

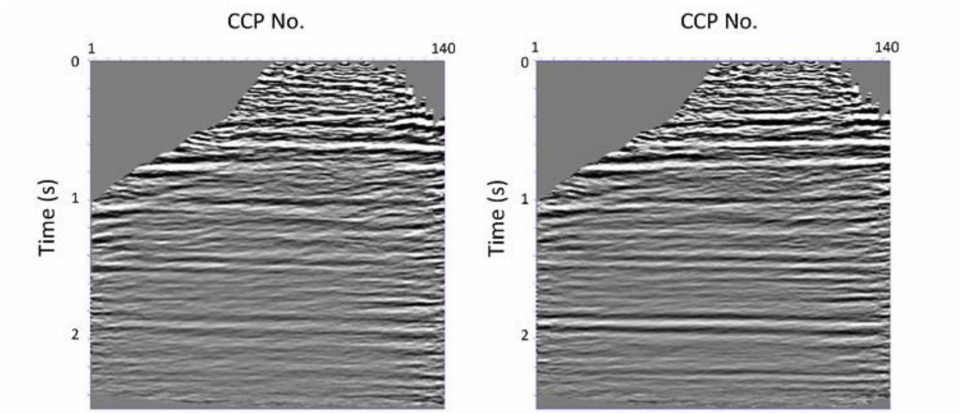

Figure 6 *(Left) One CCP crossline of the 3D dataset before S-wave static correction. (Right) The same CCP crossline after S-wave static correction by our algorithm.*

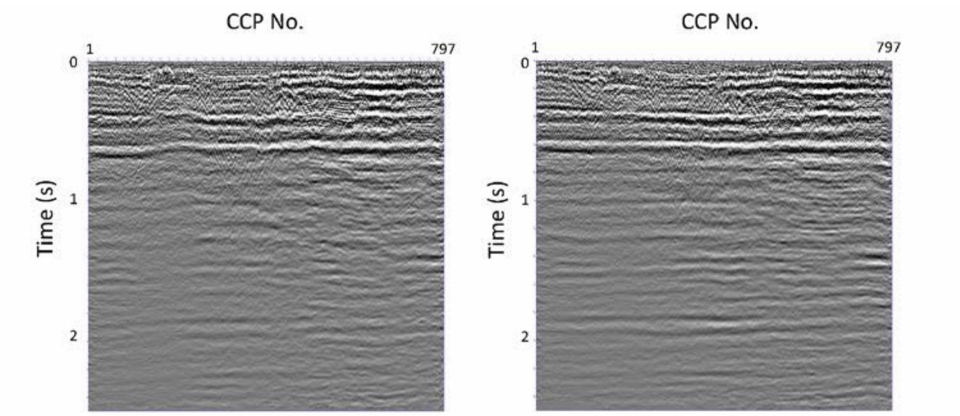

Figure 7 *(Left) One CCP inline of the 3D dataset before S-wave static correction. (Right) The same CCP inline after S-wave static correction by our algorithm.*

3D Field Data Example

We applied our algorithm on a field 3D OBC PS dataset from the Arabian Gulf. For this dataset, source-side statics (P-wave statics) had been resolved by tomography, and the only outstanding issue was the receiver-side (S-wave) statics. The PS NMO velocity was estimated from the corresponding

PP NMO velocity via V_s/V_p ratio picking. There are 12 receiver cables in this dataset, each with 200 independent receivers, and the inline and crossline distances are 50 m and 100 m, respectively. The time sampling rate is 4 ms. Suitable noise removal procedures had been carried out before application of our algorithm.

Figures 6 and 7 show one CCP crossline and one CCP inline of the dataset before and after S-wave statics correction. Clearly, the right side stacks after static correction show better reflector continuity, better alignment and better image resolution. The calculated S-wave statics are shown in Figure 8.

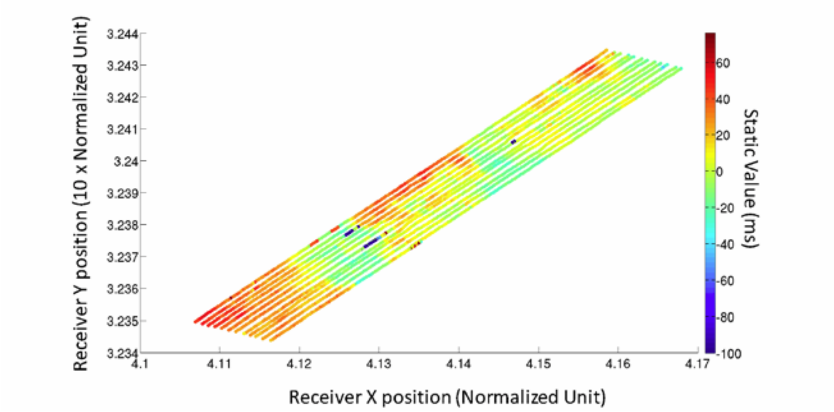

Figure 8 *Receiver-side (S-wave) statics calculated by our algorithm on this 3D PS OBC dataset.*

Conclusions

In this abstract we proposed a novel robust two-phase automatic static correction algorithm. Our new algorithm is completely data-driven and avoids intensive user input, which can not only minimize turn-around time but also eliminate human bias. One challenging synthetic dataset was used to demonstrate our algorithm, and the exact solution was obtained. One 3D PS OBC dataset was further analyzed with satisfying results achieved. We believe our new algorithm is a solid and valuable contribution to solutions of the complex near-surface problem.

Acknowledgements

The authors would like to thank Saudi Aramco for permission to publish this abstract.

References

Cox, M., Scherrer, E.F. and Chen R. [1999] *Static Corrections for Seismic Reflection Surveys.* Society of Exploration Geophysicists, Tulsa, Oklahoma.
Keho T.H. and Kelamis P.G. [2012] Focus on land seismic technology: The near-surface challenge. *The Leading Edge*, **31**, 62-68.
Nocedal, J. and Wright, S.J. [1999] *Numerical Optimization.* Springer, New York.
Rothman, D.H. [1986] Automatic estimation of large residual statics corrections. *Geophysics*, **51**, 332-346.
Sun, Y., Tonellot, T., Kamel, B. and Bakulin, A. [2014a] A Two-Phase Automatic Converted-Wave Statics Correction Method. *76th EAGE Conference and Exhibition.*
Sun Y. and Verschuur D. [2014b] A Self-Adjustable Input Genetic Algorithm for the Near-Surface Problem in Geophysics. *IEEE Transactions on Evolutionary Computation*, **18**, 309-325.
Vasudevan, K., Wilson, W.G. and Laidlaw, W.G. [1991] Simulated annealing statics computation using an order-based energy function. *Geophysics*, **56**, 1831-1839.