

We E 13

De-coupling Residual Statics and Velocity Picking

A. Darwish* (CGG), R.R. Haacke (CGG), G. Poole (CGG)

Summary

Land surveys suffer from rapid variations in velocity in the near-surface weathering layer that degrade seismic images when the velocity variations are not accounted for in imaging. While elevation information or refraction tomography can compensate for long and mid-wavelength variations, residual static algorithms are used to correct for the shorter wavelengths. Residual statics are commonly estimated by maximising lateral coherency in gathers after Normal Move-Out corrections, either by measuring trace-to-trace correlation or overall stack power. This work introduces an alternative method able to estimate residual statics using a cost function based on sparseness in gathers without a-priori knowledge about velocities needed for NMO correction. By maximizing sparsity in the tau-v and tau-p domains the method enhances coherency assuming, respectively, hyperbolic reflections in the case of mid-wavelength residual statics and local linearity in the case of shorter wavelength residual statics. Results from 2D and 3D data show overall improvement in stack power and focus, as well as reflector positioning, when the sparseness method is used before picking velocities for imaging. To complete the flow, stack optimisation methods can be run as a post-process to further add constructively to the stack.

Introduction

Variations in the thickness and velocity of shallow layers degrade the quality of onshore seismic data. Static time shifts may be applied to mitigate this deterioration for time imaging. Long-wavelength statics (greater than the acquisition spread length), and part of the mid-wavelength (comparable to the spread length), are corrected using a priori elevation data from the acquisition, or traveltimes tomography from refractions (Marsden, 1993). Remaining short wavelength statics compensate for spatially localized anomalies shorter than the acquisition spread. Residual statics algorithms use reflection data to compute time shifts that can significantly improve a time-migrated image. Residual static shifts aim to increase both stack power and focus by aligning reflection arrivals with the shape of the time-migration operator.

Prior art includes various techniques for calculating residual statics. These algorithms are known to be surface consistent, so that each shot and receiver has a unique static value according to its location (Wiggins et al., 1976). While further static shifts related to mid-point and offset can be derived in addition to the shot and receiver terms, modern processing includes these effects in the migration velocity field as far as possible. Linear inversions (Taner et al., 1974; S aghy and Zelei, 1975) compute time shifts based on maximizing cross correlations between traces. Subsequently, inversion schemes based on stack power maximization were proposed (Ronen and Claerbout, 1985), with some advantages over the cross correlation method. However, linear inversion schemes are susceptible to local minima caused by cycle skipping of the wavelet in cases where statics are large. Simulated annealing provides a non-linear inversion method suitable for the residual statics problem (Rothman, 1986; Vasudevan et al., 1991), but with potentially excessive computer cost. In recent years, non-linear inversion methods based on simulated annealing have become computationally viable (Le Meur, 2011), and thus have risen in popularity.

The above methods seek to solve a system of residual statics equations by optimising a cost function that, one way or another, evaluates lateral coherency after Normal Move-Out (NMO) correction applied to pre-stack data. Where the NMO velocity is inaccurate, however, estimated statics compensate for these errors in order to maximise stack power or lateral trace-to-trace alignment. This creates an undesired dependence between residual statics and velocities, which is partially addressed by iterative updates that cycle through velocity estimation and residual statics estimation in the processing flow. However, since both the NMO velocity picking and residual statics estimation depend explicitly on each other, it is difficult to correctly decouple these effects without trying a very large number of potential NMO velocities and solving each one for residual statics (bearing in mind that each residual static solution has to handle potential cycle skipping in the data). Where NMO velocities and residual statics are not correctly decoupled, processing geophysicists face a compound problem of incorrect NMO velocities and incorrect static shifts that lead to images with mispositioned and sub-optimally focused reflectors.

In the following, surface consistent shifts are calculated in a way where the problem of separating NMO velocity and residual statics estimation is addressed by maximising sparsity in the intercept-velocity (τ - v) domain. Assuming reflections are hyperbolic within the analysis window leads naturally to a cost function that evaluates pre-stack data coherency while allowing a large range of velocities and static shifts to be explored. In this manner both the velocity and residual static are

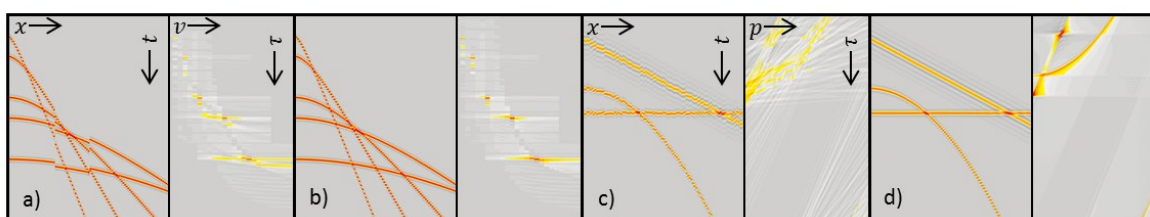


Figure 1 a) CMP gather in t - x and τ - v domains with mid-wavelength statics. b) same data after static correction. c) CMP gather in t - x and τ - p domains with short-wavelength statics. d) same data after static correction.

jointly optimised with a non-linear Monte-Carlo scheme that respects the required surface consistency of the problem. Where shorter-wavelength residual statics are required, the same approach can be applied in the intercept-slowness (τ - p) domain, which promotes sparseness in local windows of data for which reflections are assumed to be linear.

Method

To illustrate the new cost function for residual statics calculation, a synthetic Common Mid-Point (CMP) gather is shown in the time-space (t - x) and intercept-velocity (τ - v) domains with and without static shift anomalies, Figure 1a-b. As the static shifts are corrected, the τ - v data shows a clear increase in sparseness, visible as an increase in the fraction of energy contained within discrete highly-focused and small areas of the τ - v model space. By incorporating a sufficiently large velocity range in the τ - v transform it is possible to find the set of surface-consistent static corrections that maximise sparseness in this domain without a priori NMO velocity picking. The cost function, which is maximised for residual statics estimation, is evaluated as the weighted summation

$$F = \sum_s \sum_r \sum_\tau \sum_v W_{\tau,v} \left[\sum_h \psi \left(\left(\sqrt{\frac{h^2}{v^2} + \tau^2} - t_{s,r} \right), h \right) \right]^2, \quad (1)$$

where s is the set of shots, r is the set of receivers, τ is the intercept time for velocity v , h is offset, $t_{s,r}$ is the static time shift applied to data ψ in the t - x domain and W is a data dependent sparseness weight assigned to further sparsify the transform by penalising low-energy events (Hurley and Rickard, 2009). The cost function F is the weighted sum of squared amplitudes, which promotes small regions of high energy over large regions of low energy.

The cost function in (1) is optimised using simulated annealing, in which each iteration generates a random perturbation to the shot/receiver static and applies this in a surface consistent manner. As the algorithm starts to cool down the data weight further enhances focus on small high-energy regions of

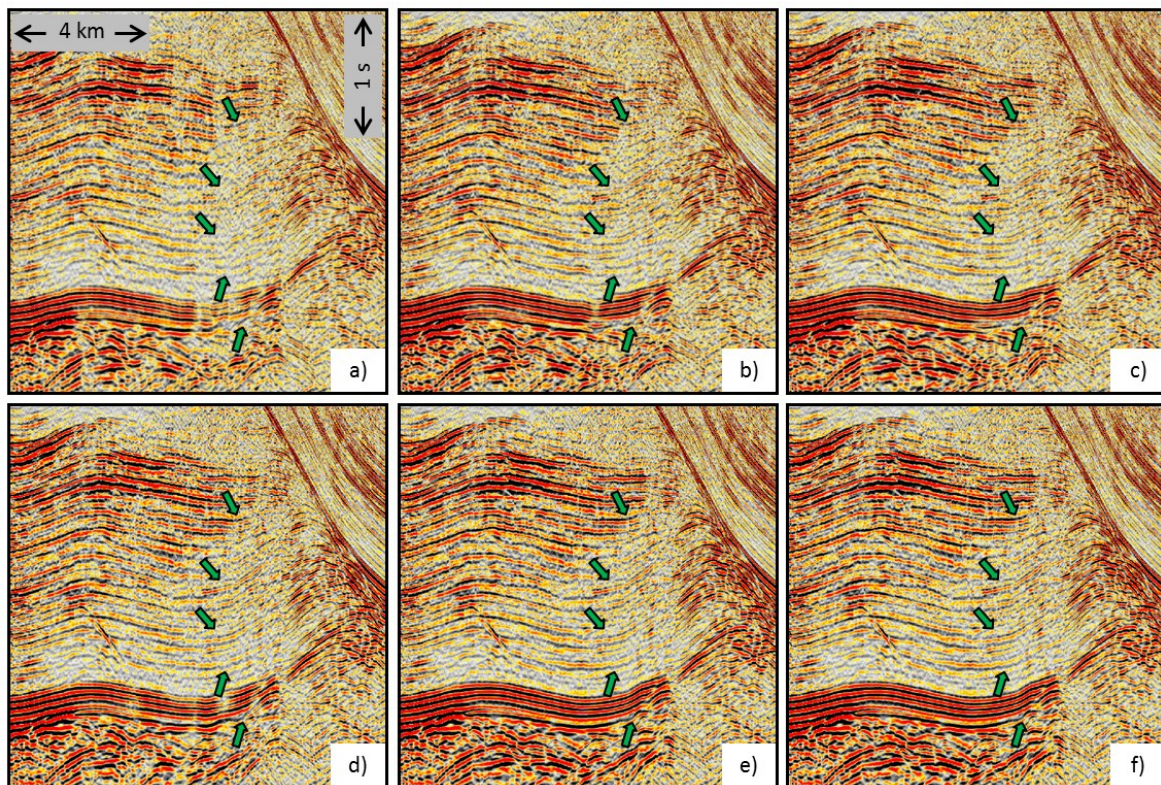


Figure 2 a) Stack with initial velocities before statics. b) With statics from stack-power optimisation applied to a). c) Velocity update on b). d) Stack with statics from sparseness optimisation. e) With velocity update on d). f) With stack-power optimisation applied to e).

model space. The final result is an optimum of sparseness given the data input to the algorithm in a user-defined time window and range of offsets chosen to satisfy the hyperbolic description of the reflections. When full convergence is achieved, the solution provides surface-consistent static shifts that maximise data coherency and which are not affected by cycle skipping of the wavelet. Although the algorithm jointly estimates statics and NMO velocity, the velocity itself is that required to model the data including both primaries and multiples. Consequently, the velocity estimation is not used to image the data since this requires primary-only velocity. A better approach is to correct the statics with the above method then estimate stacking or imaging velocity as a post-process in which multiples can be properly accounted for.

For shorter-wavelength statics, the cost function is modified to maximise sparsity in the linear intercept-slowness (τ - p) domain. The time-space processing windows are smaller for this approach, so that reflections can be described as locally linear. Figure 1c-d shows the effect of statics in the t - x and τ - p domain as short-wavelength statics are added to the data. As with the τ - v method, correctly solving for short-wavelength statics increases sparsity in the τ - p domain.

Results

The first example uses 2D data with 50 m shot spacing and 50 m receiver spacing. Figure 2a shows the stack section after manual, initial, velocity picking but before residual statics correction. Using these NMO velocities, the method of Le Meur (2011) is used to find a set of static corrections by maximising stack power. The stack shows significant uplift in resolution and event continuity (Figure 2b). Following a standard workflow, the stacking velocities are then updated after application of the residual statics (Figure 2c). Further cycles of stack-power optimisation and velocity updating are possible but not shown. In comparison, application to raw data of residual statics estimated using sparseness in the τ - v and τ - p domains produces the result in Figure 2d. This result is stacked with the initial set of velocities. The new method produces a different static solution to the stack optimisation approach, since it is not reliant on the initial set of velocities. Re-picking NMO velocities after application of residual statics leads immediately to a higher-quality result (Figure 2e), since the

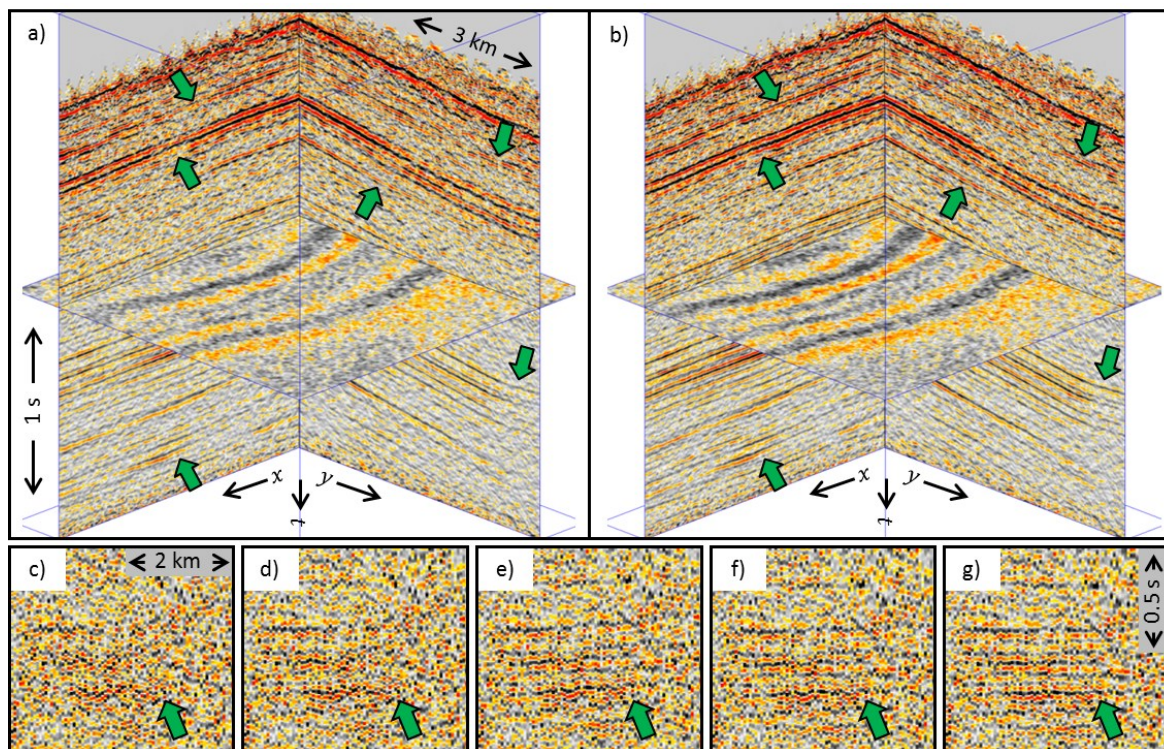


Figure 3 3D view of data before (a) and after (b) static correction by sparseness optimisation. (c) An example CMP gather after NMO with initial velocity, (d) with statics from stack-power optimisation, (e) with statics from sparseness optimisation, (f) panel (e) with new velocity, (g) panel (f) with additional statics from stack optimisation.

new velocities are not required to compensate for errors in residual statics caused by maximising stack power with the initial poorly-defined velocities. The best overall result then comes by applying stack-power optimisation to data after pre-stack sparseness optimisation and NMO correction with the updated velocities (Figure 2f).

The second example is from the Western Desert of Egypt, with orthogonal 3D geometry of 50 m shot spacing, 400 m shot-line spacing, 50 m receiver spacing and 400 m receiver-line spacing. Results show a 3D view for 200 in-lines and 250 cross-lines (Figure 3). Better resolution and continuity on the stack are obtained after applying static corrections obtained by τ - v and τ - p sparseness optimisation. Comparisons are also shown for a CMP gather (Figure 3c) where the initial NMO velocity picked without statics correction is poorly defined. Statics estimation by stack-power optimisation tries to compensate for NMO velocity errors (Figure 3d), while the sparseness optimisation (Figure 3e) finds a good set of statics corrections while preserving the velocity error in the data. This velocity is then updated (Figure 3f) with more coherent data aiding the picking. Finally, stack-power optimisation is applied to maximise focus and energy in the stack (Figure 3g).

Conclusions

Use of pre-stack sparsity in the τ - v or τ - p domains provides a powerful way to decouple residual statics from NMO velocity picking. This is due to the large range of potential velocities explored in the model space, which vastly exceed the number of velocity functions that can be explored with cycles of manual velocity picking and statics estimation based on stack power optimisation. Although computationally costly, it is possible to solve for residual statics in this way using Monte-Carlo methods to deal with cycle skipping in the data. Examples show that NMO velocities picked after applying residual statics estimated by pre-stack data sparsity optimisation better correct the focus and positioning of reflections than achieved with standard methods. Finally, stack-power optimisation methods can be used to provide final uplift to the stack where possible.

Acknowledgments

The authors thank Edison and CGG for permission to publish this paper.

References

- Hurley, N. and Rickard, S. [2009] Comparing Measures of Sparsity. *IEEE Transactions on Information Theory*, **55**(10), 4723-4741.
- Le Meur, D. [2011] Monte-Carlo Statics on Large 3D Wide-azimuth Data. *73rd EAGE Conference and Exhibition*.
- Marsden, D. [1993] Static corrections – a review, part I. *The Leading Edge*, **12**(1), 43-49.
- Ronen, J. and Claerbout, J. F. [1985] Surface-consistent residual statics estimation by stack-power maximization. *Geophysics*, **50**(12), 2759-2767.
- Rothman, D. H. [1986] Automatic estimation of large residual statics corrections. *Geophysics*, **51**(2), 332-346.
- Sághy, G. and Zelei, A. [1975] Advanced method for self-adaptive estimation of residual static corrections. *Geophysical Prospecting*, **23**(2): 259-274.
- Taner, M. T., Koehler, F. and Alhilali, K. A. [1974] Estimation and Correction of Near-Surface Time Anomalies. *Geophysics*, **39**(4), 441-463.
- Vasudevan, K., Wilson, W. G. and Laidlaw, W. G. [1991] Simulated annealing statics computation using an order-based energy function. *Geophysics*, **56**(11), 1831-1839.
- Wiggins, R. A., Lerner, K. L. and Wisecup, R. D. [1976] Residual Statics Analysis as a General Linear Inverse Problem. *Geophysics*, **41**(5), 922-938.