Monte Carlo Statics: The Last Frontier

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Abstract

Summary

Most surface-consistent (SC) residual statics estimations are based on the results of cross-correlation functions and use an inversion with a linear system that can produce solutions trapped in a local minimum. In order to find the solution at the global minimum, we present a non-linear approach based on a Monte Carlo method within a simulated annealing scheme using pre-stack data rather than the result of cross-correlation functions. The efficiency and the robustness of this method to compute SC residual statics will be demonstrated on synthetic, real 2D and 3D data examples.

Introduction

Conventional approaches to evaluate SC residual static corrections are mostly based on the result of cross-correlation functions using a linear inversion scheme. Rothman (1986) and Vasudevan (1991) showed that the estimation of large statics is better handled with a non-linear scheme based on a Monte-Carlo method within a simulated annealing approach. In this method, a calculation is repeated many times by using a number of random possible values whose result gives an estimate for a solution at the global minimum. Even though promising results were obtained in the 1980's and 1990's, this non-linear method has not been adopted by the industry on a large scale due the highly expensive computation cost. Nowadays, using the available huge computer power to estimate the SC residual statics, one can use this non-linear approach in 2D and 3D surveys at a reasonable cost.

Technical overview

Different methods are used to compute the SC residual statics (Ronen and Claerbout, 1985, Marsden, 1993). Most of these methods are based on the results of the cross-correlation functions and use a linear system approach that should converge to a local minimum. The Simulated Annealing concept has been introduced by Kirkpatrick et al. (1983) based on a Monte-Carlo technique devised by Metropolis et al. (1953). Rothman (1985) has adapted this concept to the computation of the residual statics to find a solution at the global minimum. The process of the simulated annealing is used for algorithms based on an analogy between optimization and the

growth of long-range order, such as the growth of large crystals in a slowly cooling melt (Sheriff, 2002). Here, the melt solution is replaced by a cost function based on the energy that will suddenly increase (crystallization) when a certain set of statics and temperature scheme is raised (cooling schedule). Different kinds of cost functions could be used, based on either the stack power (Rothman, 1986) or the coherence of the neighbouring CMP gathers to optimize the reflections on the final CMP stack (Vasudevan et al., 1991).

In this study, the Monte-Carlo method used within the simulated annealing approach is an updated version of the objective function published in Vasudevan et al. (1), which gives more stable and robust results.

$$(1) \quad E = -C = -\sum_{y}\sum_{t}\{\sum_{h} d_h^y[t + s_{i(y,h)} + r_{j(y,h)}]\} \times \{\sum_{h} d_h^{y+1}[t + s_{i(y+1,h)} + r_{j(y+1,h)}]\}$$

The cooling schedule (2) is computed as a function of the iterations (t) and initial temperature T_0 where T_0 is a function of the initial RMS energy (RMS_0).

$$(2) \quad T(t) = \alpha^t . \beta . RMS_0$$

Each iteration processes every shot and receiver randomly to avoid bias or cycle-skipping (Dahl-Jensen, 1989). For each selected shot or receiver, a random value is chosen in a pre-defined static range and applied to the pre-stack data. The difference in the energy function between the new and old state is computed ($\Delta E = E_{new} - E_{old}$) which reflects the fluctuation of the coherence in the CDPs. If ΔE is negative the static shift is automatically accepted. If ΔE is positive, the decision to keep it or not is made using the Metropolis criteria (3):

$$(3) \quad p = \exp(\frac{-\Delta E}{T})$$

Each iteration is completed when every shot and receiver has been processed once. Maintaining the cooling schedule, hundred iterations are necessary to obtain a jump in the energy function, which characterizes the crystallization stage. The process continues with additional iterations until minor changes in shot and receiver statics are observed.

Data examples

Firstly, the Monte-Carlo method within the simulated annealing approach was calibrated on 2D synthetic data. Then, this process was applied on real 2D and 3D data from the Canadian Foothills and Northern Alberta where successful results were achieved.

A 2D pre-stack synthetic data with 4 flat events was generated by adding of various noise levels (Fig.1a). Before starting the computation of the SC Monte-Carlo statics process, a random perturbation was applied to each shot and receiver (between a range of $\pm$ 20 ms). The goal of this test was to estimate a set of SC residual statics to correct the data from the initial perturbation to the original 4 flat interfaces. CMP stacks were computed using static values obtained at different iterations (Fig. 1b-e). The change in the stack power through the iterative process is underlined by the energy function versus the number of iterations. Until a hundred iterations, the energy level stays low (Fig.1b) providing non-optimal SC residual static values and a defocused CMP stack. When the crystallisation stage is started (from ~100 to ~150 iterations), a jump of energy is underlined by a better set of statics and stack image (Fig.1c & Fig.1d). After the crystallisation

phase, the energy curve reaches a plateau where the SC residual statics when applied creates a stack back to the original 4 flat events (Fig.1e).

The second data set was a 2D line from Canadian Foothills; a CMP stack was obtained by applying SC residual statics derived from our conventional tools (Fig. 2a). This section was used as a reference to compare to the SC Monte-Carlo statics.

This data set contains 542 CMP gathers (with a maximum fold of 14 traces) with 69 shots and 253 receivers. A static range within ± 40 ms was chosen as well as a temperature schedule based on the initial RMS energy. Figure 2b shows the shape of the energy function versus the number of iterations. During the crystallization phase, (iteration 1 to 200), the presence of troughs (black arrows) is observed corresponding to local minima. Because this process is non-linear and a temperature schedule high enough, the algorithm is able to escape from these local minima to search for the global minimum. After the crystallization phase, a high energy level is reached producing optimal static values at the global minimum (Fig. 2b). A comparison of the Monte-Carlo statics with the conventional solution shows a similar shape but with more high frequency resolution with the Monte-Carlo method (Fig. 2c). The quality of the stack obtained with the Monte-Carlo statics shows dramatic improvements (Fig. 2d): the resolution of the main reflector is improved; the better continuity of the thin layers above the main reflector and the apex and curvature of the diffracted hyperbola is more focussed (right hand side of the section).

The last data example was a 3D data coming from the Northern Alberta. This data contains 12165 CMP gathers (with a maximum fold of 45 traces) with 502 shots and 512 receivers. Shot and receiver lines were roughly perpendicular with irregular X,Y locations. A 3D implementation of the objective function was done. A 3D view of initial data set without SC residual static corrections shows discontinuous events with a lack of resolution in the three directions (Fig. 3a). The application of the SC Monte-Carlo residual static corrections brings more continuity and resolution of the main reflectors in the three dimensions (see black arrow locations) (Fig. 3b), highlighted in the time slice showing sharper boundaries between high and low amplitudes.

Conclusions

The Monte Carlo method within the simulated annealing process is a very powerful approach to compute SC residual statics. Combining realistic search restrictions, robust objective function and machine resources, this non-linear approach is the tool to obtain a set of SC residual statics at the global minimum. Examples in this paper show a significant benefit we have applying this technique to obtain a sharper image for 2D and 3D land data.

References

Dahl-Jensen, T.,1989. Statics corrections on crystalline rocks: Geophys. Prosp., **37**, 467-478.

Kirkpatrick, S., Gelatt, C. D., Jr., and Vehhi, M. P., 1983. Optimization by simulated annealing, Science, **220**, 671-680.

Marsden, D.,1993, Static corrections – a review, partIII: The Leading Edge, 12, 210-216.

Metropolis, N., Rosenbluth, A., Rosenbluth, M. Teller, A., Teller, E., 1953. Equation of state calculations by fast computing machines, J. Chem. Phys., **21**, 1087-1092.

Ronen, J., Claerbout, J. F., 1985. Surface-consistent residual statics estimation by stack power maximization, Geophysics, 50, 2759-2767.

Rothman, Daniel H., 1985. Non linear inversion, statistical mechanics, and residual statics estimation, Geophysics, VOL 50, NO. 12 (December 1985); p. 2784-2796.

Rothman, Daniel H., 1986. Automatic estimation of large residual statics corrections, Geophysics, VOL 51, NO. 2 (February 1986); p. 332-346.

Sheriff, R.E, 2002, Encyclopedic Dictionary of Applied Geophysics, fourth edition, SEG.

Vasudevan, K., Wilson, W. G., and Laidlaw, W. G., 1991. Simulated annealing statics computation using an order-based energy function, Geophysics, VOL. 56, NO. 11 (November 1991); p. 1831-1839.
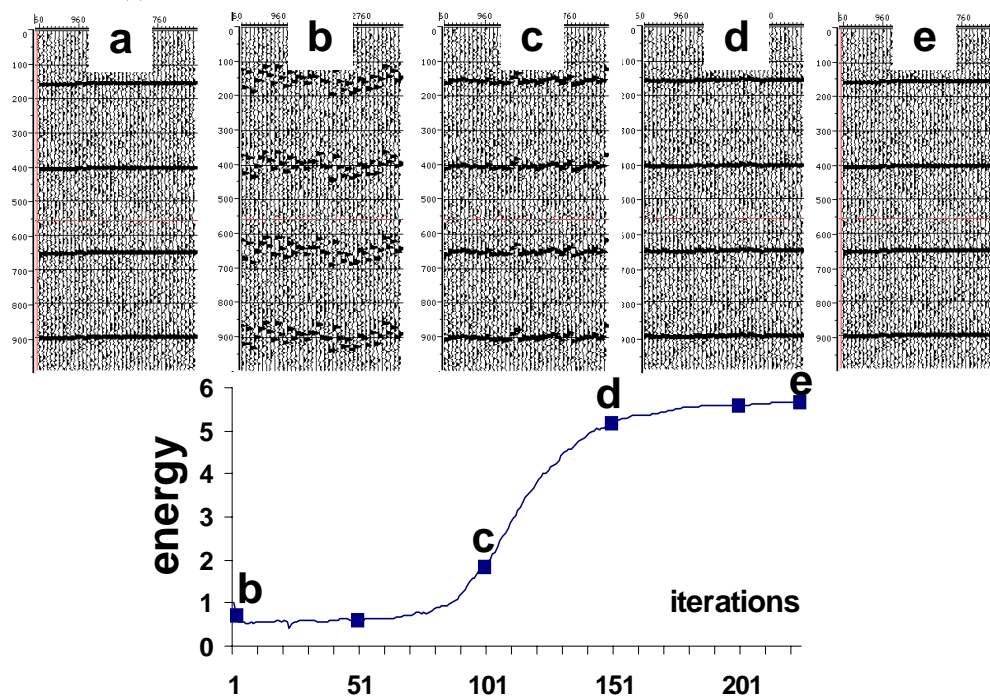
Figure 1. a. CMP stack of the initial data. From b. to e:The energy function and the associated CMP stack section at different stages. (b) 2 iterations; (c) 100 iterations; (d) after 150 iterations; (e) after 218 iterations (final solution).
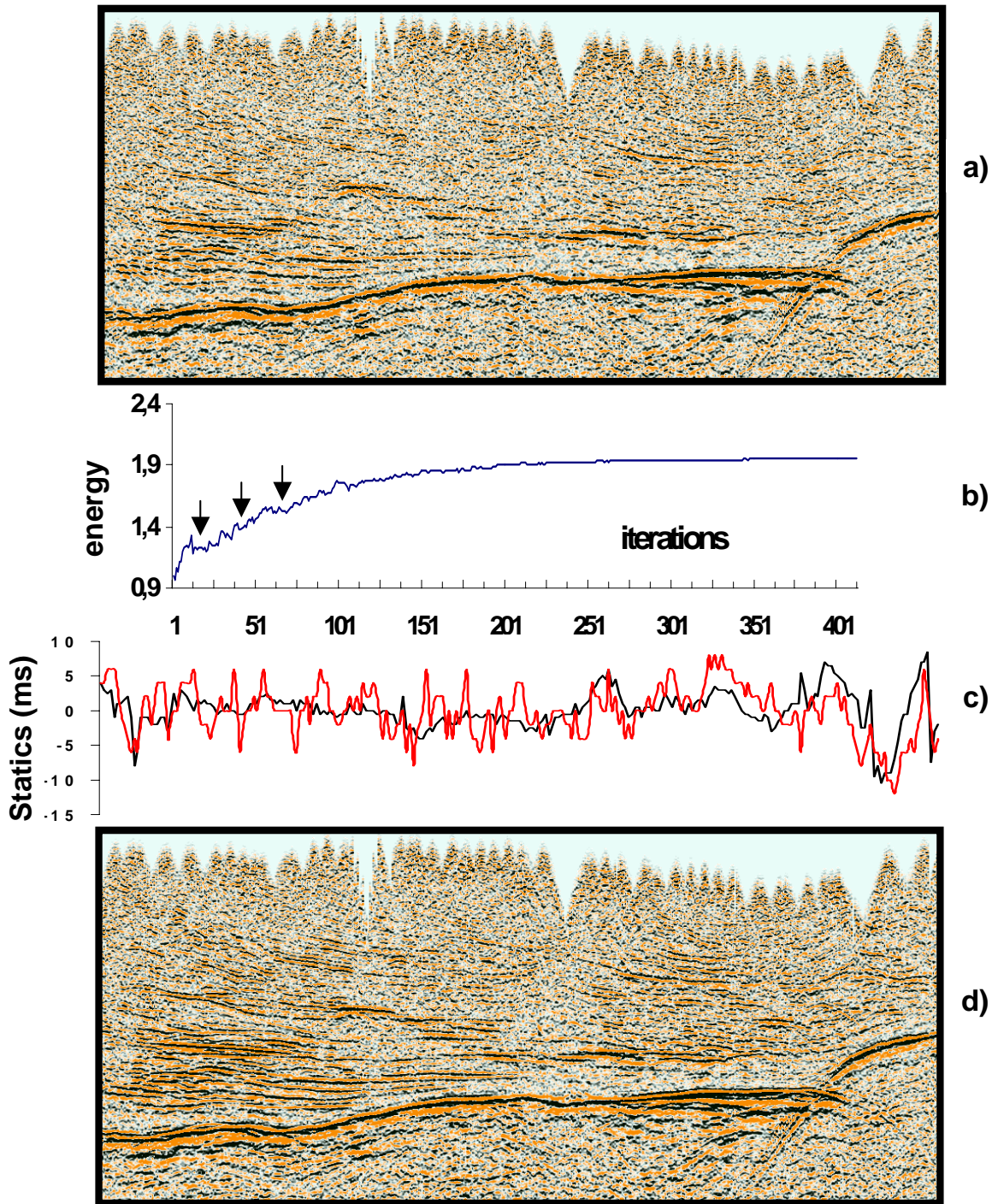
Figure 2. (a) CMP stack section with the conventional SC residual statics, (b) energy function versus the number of iterations, (c) SC residual statics corrections, in black the conventional solution and in red the Monte-Carlo solution, (d) CMP stack section with the Monte-Carlo residual statics.
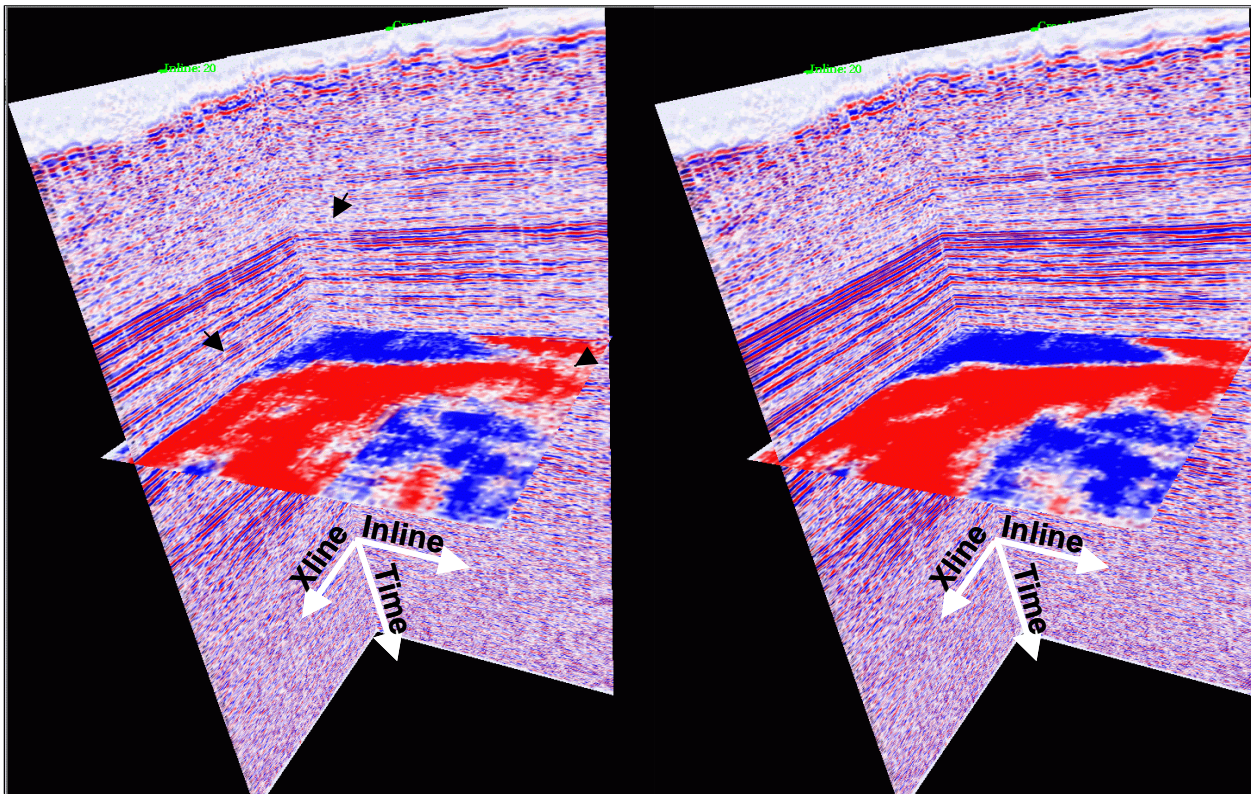
Figure 3. 3D data example: (a) 3D data view of the initial volume without SC residuals statics, (b) 3D data view with the SC Monte-Carlo static solution.