WS11-B01

Simultaneous CRS Parameters Search Based on a Non-linear Conjugate Gradient Method with Preconditioning

S. Dell* (CGG)

SUMMARY

Multi-parameter methods, e.g., Common-Reflection-Surface (CRS) stacking, have become popular because they exploit increased data fold compared to conventional CMP processing, resulting in an improved signal-to-noise ratio and, thus, enhanced images. However, these methods require additional effort since they incorporate more stacking parameters than CMP processing. The simultaneous brute-force search for all parameters is still not common because the increase in computer performance is countered by an increasing amount of acquired data (the amount grows faster than Moore's law). An optimization method can therefore serve as an alternative to the global (brute-force) approach since it reduces the number of evaluations of the coherence functional (e.g., semblance) significantly. I propose to use a non-linear conjugate gradient method to estimate the CRS attributes. The method utilizes the secant method, the Polak-Ribière formula, and preconditioning. I applied this approach to a complex marine dataset which led to more focused stack results than using the traditional pragmatic CRS attribute search.

Introduction

Stacking operators represent an approximation of traveltime moveout and can be parameterised with one or several parameters. A multi-parameter, multi-dimensional stacking operator performs the stacking process in two directions (i.e., midpoint and offset) while a single-parameter, one-dimensional operator performs the stacking in one direction only (i.e., offset). The well-known process of common midpoint (CMP) stacking in its basic form is an example of a method that uses a single-parameter operator. On the other hand, the common-reflection-surface (CRS) stack (see, e.g., Jaeger et al., 2001) employs a multi-parameter operator. The zero-offset CRS operator is parameterised by three (2D case) or eight (3D case) parameters. These parameters control the fit of the operator to the prestack data and, in practice, are determined by a coherence analysis. Usually, a brute-force search on a sufficiently dense grid is conducted to find the best-fitting stacking parameters. Such a search requires already for a typical 2D line more than 10^{12} semblance evaluations (Hertweck et al., 2007). Though computational performance is steadily increasing, this search is very time-consuming, cumbersome and cost ineffective. Therefore, a pragmatic search strategy has been proposed to estimate CRS parameters. It is based on splitting the simultaneous multi-parameter search into three sequential searches for one parameter (2D) or two and three parameters (3D), respectively. The step-by-step strategy, however, may lead to suboptimal parameter estimates resulting in a suboptimal CRS stack. A multi-parameter search, which is based on an optimization method, can serve as an alternative to the brute-force approach since it greatly reduces the number of evaluations of the semblance functional.

Any optimization method evaluating the functional maximum can be used, e.g., simulated annealing (Garabito et al., 2012) or conjugate direction method (Bonomi et al., 2009). I propose to use a non-linear conjugate gradient method because it is faster and produces smooth parameter estimates. The proposed approach is based on the secant method and Polak-Ribière formula with preconditioning (Shewchuk, 1999).

Theory

The zero-offset CRS stacking operator is given by equation (1) where time t_0 represents the zero-offset time, h is the half offset, m is the midpoint displacement, and p, M, N are CRS stacking parameters estimated by a coherence (here semblance) analysis:

$$t = \sqrt{(t_0 + 2pm)^2 + Mm^2 + Nh^2} \qquad (1)$$

The CRS stacking parameters are scalars in the 2D case and a vector and matrices in the 3D case.

The basic idea of the conjugate gradient method is that the minimization of a quadratic function f

$$f(x) = \frac{1}{2} xAx - bx + c \qquad (2)$$

is equivalent to the solution of the following problem:

$$Ax = b \quad or \quad x = A^{-1}b \qquad (3)$$

Usually, one starts at an initial point x_0 and reaches the solution (or close enough approximate of it) taking a series of steps x_1, x_2, x_3 and so on. Taking a step one chooses the direction opposite to the gradient of the function. In the non-linear gradient method the computation of the step along the direction of the steepest descent, α, and step along the search vector, β, is not a trivial task. However, just like for the linear conjugate gradient method a value of the step α is found by ensuring that the gradient is orthogonal to the search direction. To calculate the step β we use the secant method and Polak-Ribière formula given by

$$\beta_{i+1} = \frac{r_i^T (r_{i+1} - r_i)}{r_i^T r_i} \quad , \qquad (4)$$

where r is the residual vector.

Non-linear conjugate gradient can also be preconditioned by choosing a pre-conditioner that approximates the Hessian. A linear pre-conditioner attempts to transform the quadratic form so that it is similar to a sphere for a region close to x_i (Nocedal and Wright, 1999).

Example

To test the method, I applied it to a complex marine data example. Firstly, I performed a conventional step-by-step CRS parameter search. I used reasonable scan apertures and a velocity guide. With the estimated parameters I performed the final CRS stack (Figure 1a). Then I performed the optimized CRS parameter search based on the method introduced above. As initial values I used CRS parameters estimated by the step-by-step search, perturbed by five percent. I used ten search iterations. Each search iteration includes five refinements of β. As a stop criterion I either used reaching the maximum number of iterations (i.e., 10) or dropping tolerance error below the threshold. With the estimated parameters I performed the final CRS stack (Figure 1b). I kept the aperture for the parameter scan and for the final stack the same for both the pragmatic and optimized CRS method.

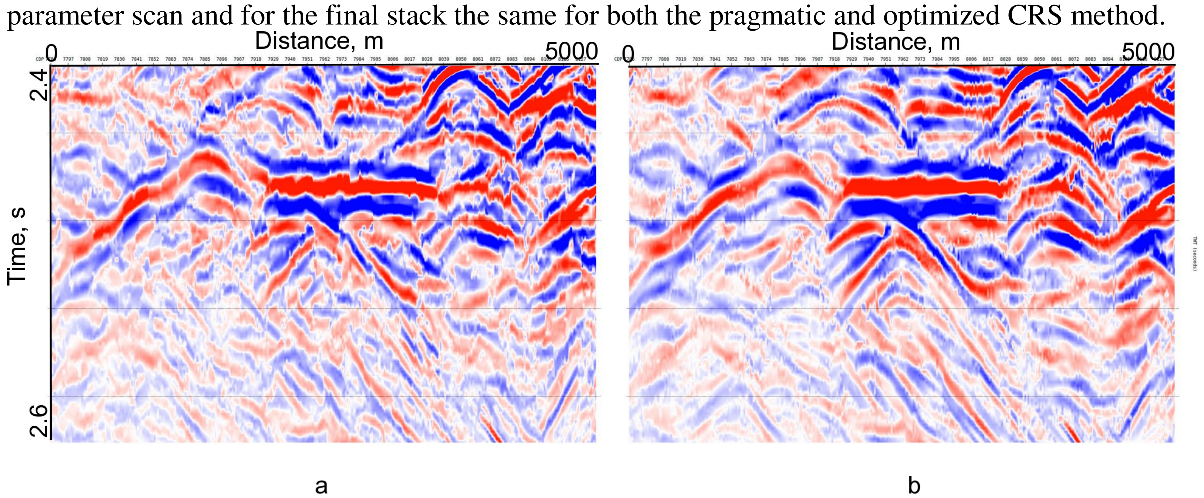

Figure 1 *The figure shows the CRS stack produced by the step-by-step search (a) and optimized search (b). Seismic events are more continuous and better focused by the optimized CRS stack in (b).*

Conclusion

I have presented a new approach to perform the CRS parameter search. This approach is based on a non-linear conjugate gradient method with preconditioning. The optimized search was performed including all CRS parameters making it more robust and producing better results than the pragmatic search strategy based on the step-by-step approach.

Acknowledgements

I thank CGG for permission to publish this work. I am grateful to Fugro and Finder Exploration for permission to show the data. I also thank my R&D colleagues at CGG for continuous support.

References

Bonomi, E., Cristini, A.M., Theis, D. and Marchetti, P. [2009] 3D CRS analysis: a new data-driven optimization for the simultaneous estimate of the eight parameters, *SEG annual meeting,* **28.**

Garabito, G., Stoffa, P.L., Lucenca, L.C. and Cruz, J.C.R. [2012] Part I – CRS stack: Global optimization of the 2D CRS-attributes. *Journal Applied Geophysics*, 92-101.

Hertweck, T., Schleicher, J. and Mann, J. [2007] Data stacking beyond CMP. *The Leading Edge* **26**(7), 818-827.

Jaeger, R., Mann, J., Hoecht, G. and Hubral, P. [2001] Common-reflection-surface stack: Image and attributes: *Geophysics*, **66**(1), 97–109.

Nocedal, J. and Wright, S.J. [1999] *Numerical optimization*. Springer Verlag, New York.

Shewchuk, J.R. [1999] *An introduction to the conjugate gradient method without the agonizing pain*. Carnegie Mellon University, Pittsburg.