3D general surface multiple prediction: An algorithm for all surveys

Bill Dragoset, WesternGeco, Ian Moore, Schlumberger Cambridge Research, Margaret Yu, Wei Zhao and Alex Cooke*, WesternGeco

Abstract

3D general surface multiple prediction (GSMP) is a data-driven 3D SRME algorithm that solves the problem of trace sparseness. Rather than overcoming the sparseness problem by changing the data to fit the algorithm – for example, by means of regularization and interpolation – GSMP changes the SRME algorithm to fit the data. This not only makes GSMP a universal compute engine for the 3D prediction of multiples, but also makes it quite versatile. We illustrate this versatility by showing successful applications of GSMP to narrow-azimuth, wide-azimuth, and rich-azimuth seismic surveys.

Introduction

In recent years, the seismic industry's repertoire of practical marine survey designs has increased dramatically. In particular, an effort to improve subsurface images in complex areas has led to narrow-azimuth (NAZ) streamer surveys being replaced by multi-azimuth (MAZ), wide-azimuth (WAZ), and rich-azimuth (RAZ) surveys. One mechanism by which such surveys are expected to improve images is the inherent multiple attenuation of a many azimuth stack. Indeed, Kapoor et al. (2007) have reported that WAZ data without multiple attenuation can produce better quality images than NAZ data with multiple attenuation. On the other hand, the same authors also point out that many-azimuth datasets still benefit from residual multiple attenuation. Thus, in spite of the industry's fondest hopes, it seems that even with MAZ, WAZ, and RAZ surveys, we should not dispense with multiple attenuation. Ideal 3D surface-related multiple elimination (SRME) is a data-driven process in which seismic traces are manipulated to predict surface multiples (van Dedem and Verschuur, 2001). For each input trace, selected pairs of traces are convolved to obtain a 3D volume called a multiple contribution gather (MCG) (Figure 1a). Stacking an MCG then produces the predicted multiples for the targeted input trace. Unfortunately, ideal 3D SRME requires far more traces and a far different distribution of traces than are recorded in any marine survey. 3D general surface multiple prediction (GSMP) overcomes the sparse trace distribution problem quite effectively (Moore and Dragoset, 2008). The basic concept of GSMP was first published in 2005 (Bisley et al., 2005). Since then, Kurin et al. (2006) have described an approach similar to GSMP, and also Ceragioli et al. (2007) have briefly mentioned the basic GSMP concept.

Although it was initially envisioned as a way to address feathering issues in NAZ surveys, GSMP is equally applicable for MAZ, WAZ, and RAZ datasets. In this paper, we demonstrate the algorithm's versatility, showing results from NAZ, WAZ, and RAZ surveys.

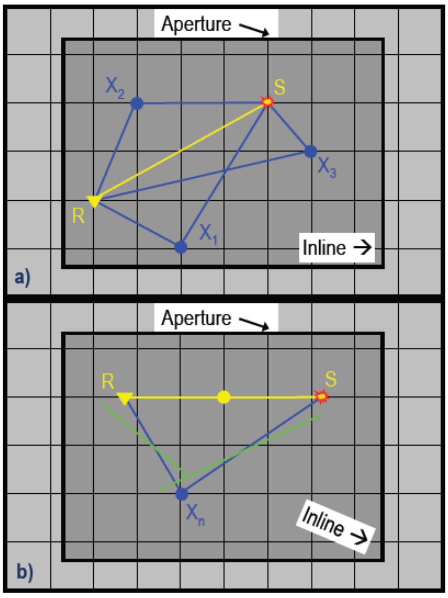

Figure 1: Plan views of ideal 3D SRME and GSMP.
a) In ideal 3D SRME, data are assumed to be completely regular so that the end points R and S of each target trace (yellow line) fall on the nodes of a fixed grid oriented in a fixed direction. Each grid node in the aperture is considered a possible downward reflection point (DRP); there are three are shown here, represented by Xs. The contribution of the nth DRP to an MCG is computed by convolving the corresponding traces RXn and SXn (blue lines), both of which must exist in the input dataset.
b) In GSMP, the aperture grid is redefined for each target trace, based on its midpoint (yellow circle) and azimuth. The input to GSMP is a non regularized, noninterpolated field dataset. Because, in general, the traces RXn and SXn required for the nth convolution will not exist in the input dataset, a nearest-neighbour search selects the most suitable alternatives (green lines) from among the traces that are present.

GSMP Method

The GSMP algorithm is as follows:

1. Input all recorded traces along with nominal velocity functions. Compute the midpoint, offset, and azimuth of each trace.
2. Select a target trace and define the aperture and computational grid (Figure 1b) for that trace.
3. For each grid node in the aperture, use a nearest neighbour search to select from among the input traces the two best traces for that convolution.
4. Compensate the two selected traces for offset errors using differential normal moveout.
5. Convolve the two traces and store the result.
6. Return to Step 3 until all grid nodes in the aperture are processed.
7. Stack the MCG.
8. Return to Step 2 until multiples are predicted for all input traces.

The nearest-neighbour search in Step 3 is accomplished by finding the input trace among all input traces that has the minimum error, E, expressed as a Euclidian distance, between it and the desired trace. Several choices for the error metric are possible, each having certain advantages and disadvantages for particular survey characteristics. An example error metric is:

$$E2 = \{W_h\,(h_D - h_I)\}^2 + \{W_a\,(\alpha_D hD - \alpha_I h_I)\}^2 + \{W_x\,(x_D - x_I)\}^2 + \{W_y\,(y_D - y_I)\}^2 + \{W_q\,Q_I\}^2$$

In this equation, h, α, x, and y represent offset, azimuth, and the two midpoint coordinates, respectively. The subscripts D and I refer to the desired trace and an input trace. The Ws are weights that govern the relative importance of the five terms in the error to the nearest-neighbour search. The fifth term allows discrimination against input traces of poor quality, Q, where Q is, for example, proportional to the amount of noise in a trace.

Note that the second term involves azimuth scaled by offset, which is reasonable because reflected events become less sensitive to azimuth as offset decreases. GSMP's on-the-fly interpolation accomplished by the nearest-neighbour search solves many problems associated with SRME. For example, a common problem in 2D and 3D SRME is MCG aliasing caused by coarse spatial sampling in the acquisition (Dragoset et al., 2006). With GSMP, one can adjust the spacing of the grid nodes to minimize MCG aliasing without having to make any corresponding changes to the input data. Missing near-offset traces is another common SRME problem. We have found that GSMP's interpolation is robust enough that extrapolating missing near offsets is often unnecessary. Particular metrics and weights can be chosen to match particular survey situations, such as: whether multiples are related mostly to specular reflections or diffractions, the predominant dip direction relative to the survey direction, whether the survey is narrow azimuth or many-azimuth, and others. This makes GSMP capable of producing excellent results for a wide variety of datasets without applying any specialized pre-processing to the input data.

Field Data Examples

Figures 2 through 5 show close-up views of GSMP results for NAZ, WAZ, and RAZ surveys acquired in the deepwater Gulf of Mexico. Each figure is accompanied by a small rose diagram that shows the distribution of offsets and azimuths that were recorded during the survey. In each case, GSMP made use of the available traces in its multiple prediction. Also in each case, preliminary testing was done to select optimal GSMP parameters, such as aperture size, grid node spacing, and weights for the error metric.

The excellent multiple attenuation in the examples from a variety of survey designs illustrates the versatility of the GSMP algorithm. Of particular interest is Figure 4, which shows that application of GSMP produces significant improvement, even for a wide-azimuth stack. Although not shown in this abstract, comparisons of multiples predicted by GSMP with those predicted by 2D SRME as well as various other methods of 3D SRME show that GSMP predictions provide the best match to actual multiples

Conclusions

3D general surface multiple prediction (GSMP) is a data-driven process that overcomes the trace sparseness problem faced by ideal 3D SRME. It accomplishes this by an on-the-fly interpolation procedure, which means that dataset preprocessing steps, such as regularization, interpolation, and extrapolation, are not required. GSMP employs a weighted, nearest-neighbour search algorithm that chooses which two traces to convolve for any particular downward reflection point. This feature gives the algorithm the versatility to predict accurate multiples for a wide variety of survey acquisition geometries. The versatility and quality of GSMP multiple attenuation is illustrated in this paper by application to narrow-, wide-, and rich-azimuth surveys from the deepwater Gulf of Mexico. In all cases, the multiples were well attenuated with minimal impact on primary reflections.

Acknowledgments

We thank BHP Billiton, Hess Corp., and Repsol-YPF for permission to show the Shenzi results (Figure 5), and WesternGeco for permission to publish this paper.

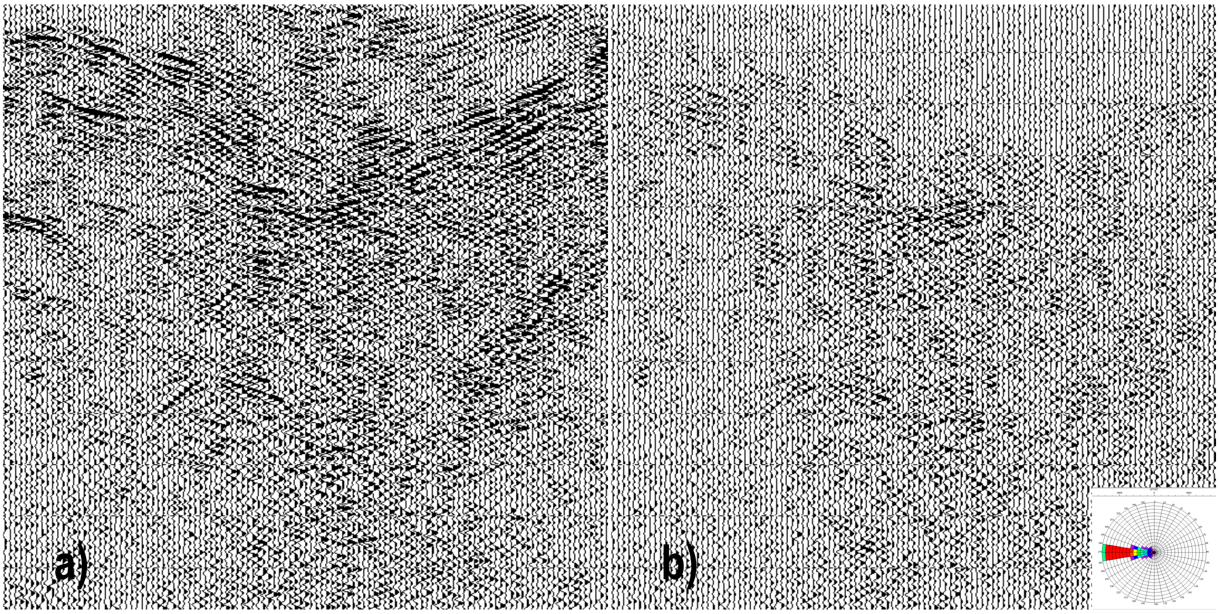

Figure 2: Close-up view of a 5010-m common offset from a narrow-azimuth survey. a) Without multiple attenuation. b) With 3D general surface multiple prediction (GSMP). The SRME class of algorithms often finds longer offsets more challenging than shorter offsets. For this survey, however, GSMP produced excellent results at all offsets. The small rose diagram in this and subsequent figures shows the distribution of azimuths and offsets recorded by the survey.

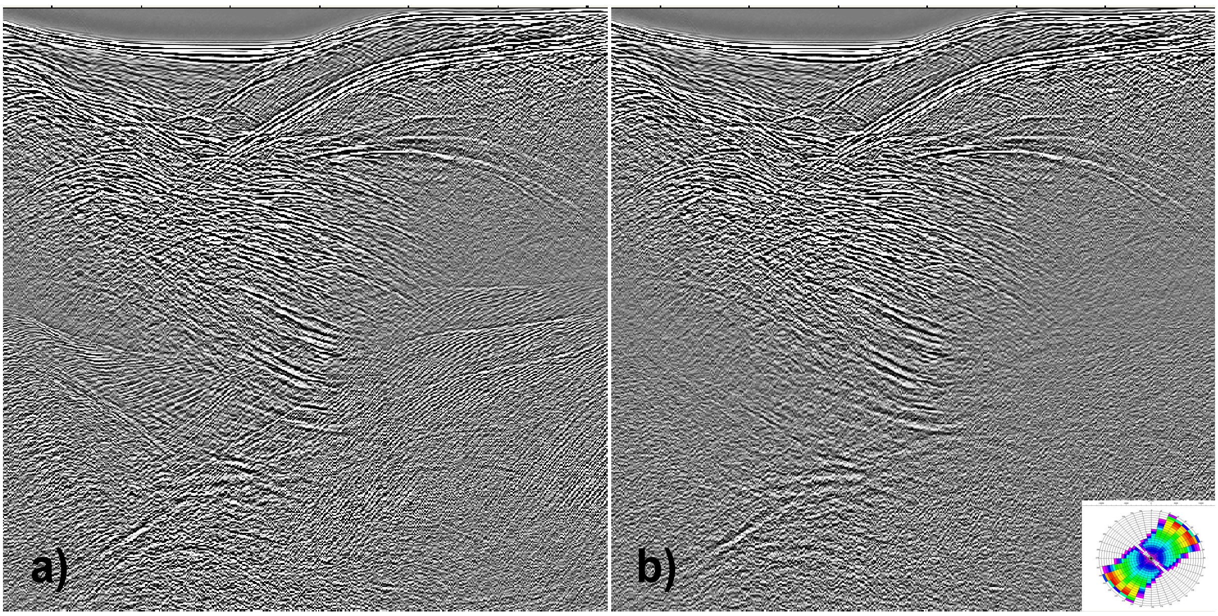

Figure 3: Portion of a stack from a wide-azimuth survey. a) Without multiple attenuation. b) With GSMP multiple attenuation. Note in particular the successful removal of multiples in the center of the section without disturbance to the primary reflections.

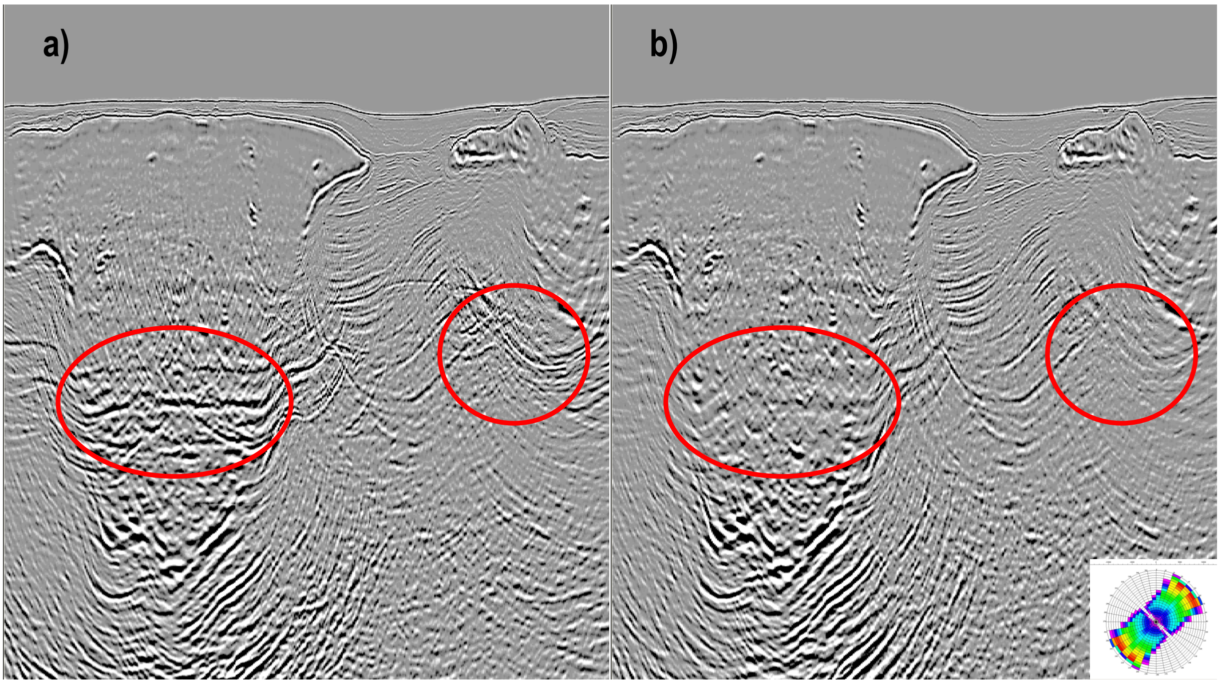

Figure 4: 3D depth-migrated images from the dataset shown in Figure 3. a) Without multiple attenuation. b) With GSMP multiple attenuation. The red circles enclose areas where it is easy to see the impact of GSMP on the migrated image.

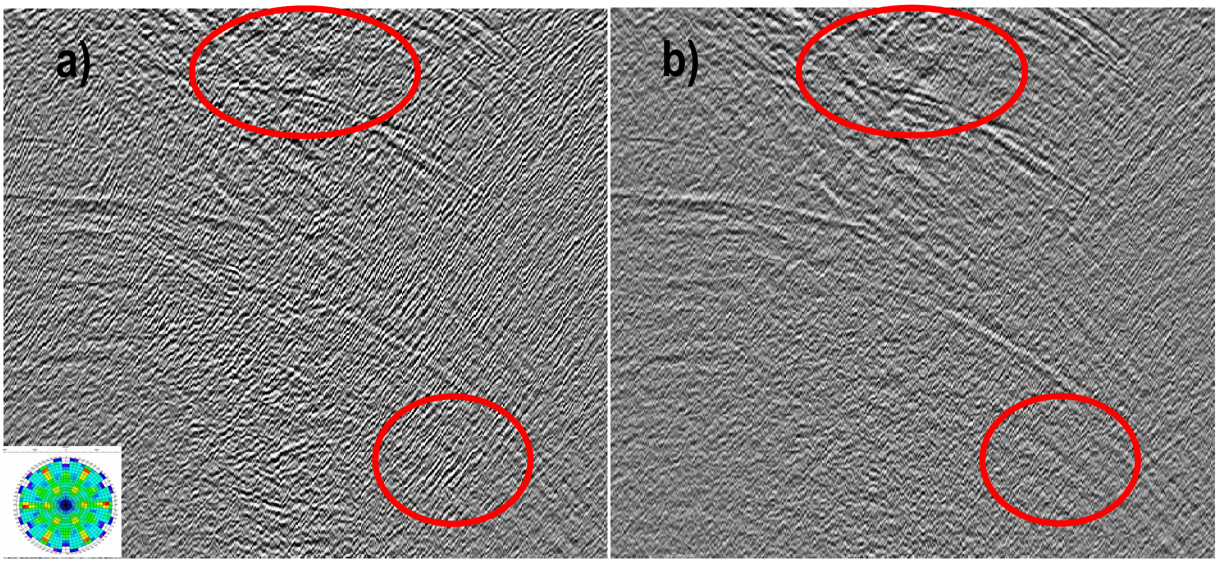

Figure 5: Stacked data from a rich-azimuth survey. a) Without multiple attenuation. b) With GSMP multiple attenuation. The red circles enclose areas where it is easy to see the impact of GSMP. (Courtesy of BHP Billiton, Hess Corp., and Repsol-YPF.)

References

Bisley, R., I. Moore, and W.H. Dragoset, 2005, Generalized 3D surface multiple prediction: PCT patent application publication WO 2005/103764.

Ceragioli, E., A. Melois, and P. Hugonnet, 2007, Wide azimuth feasibility study – Key processing considerations for an optimum design: 69th Conference and Exhibition, EAGE, Expanded Abstracts, C011.

Dragoset, B., I. Moore, and C. Kostov, 2006, The impact of field-survey characteristics on surface-related multiple attenuation: Geophysical Prospecting, **54**, 781–791.

Kapoor, J., M. O'Briain, D. Desta, I. Atakishiyev, and M. Tomida, 2007, Subsalt imaging – The RAZ/WAZ experience:77th Annual International Meeting, SEG, Expanded Abstracts, 926-930.

Kurin, E., M.S. Denisov, and D. Lokshtanov, 2006, A method for 3D surface-related multiple prediction in case of coarse sampling: International Conference and Exhibition St. Petersburg, EAGE, B032.

Moore, I. and B. Dragoset, 2008, General surface multiple prediction (GSMP): A flexible 3D SRME algorithm: 70th Conference and Exhibition, EAGE, Expanded Abstracts, G043.

van Dedem, E.J. and D.J. Verschuur, 2001, 3D surface multiple prediction using sparse inversion: 71st Annual International Meeting, SEG, Expanded Abstracts, 1285-1288.