

# Large dip artifacts in 1.5D internal multiple prediction and their mitigation

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# **Summary**

Internal or interbed multiples can be predicted and attenuated from reflection data using a method derived from the inverse scattering series. The involves a parameter  $\epsilon$  which limits the nonlinear data combinations used in the prediction. Large dip numerical artifacts, noticeable in unfiltered 1.5D predictions, are traceable to the use of a single value of  $\epsilon$  for every lateral wavenumber in the input data. Here we demonstrate that these artifacts can be mitigated with an  $\epsilon$  which is a linearly increasing function of  $k_g$ . The results are a slight improvement over those obtained by ad hoc filtering, but beyond this we argue the  $\epsilon(k_g)$  approach is preferable, in that it is tied to our interpretation of the origins of the artifacts.

#### Introduction

Luo and co-authors in a recent Leading Edge article point out that most technical successes relating to multiple removal have been reported in marine settings (Luo et al., 2011). Technical challenges associated with land environments, where internal multiples are a significant impediment to interpretation, have led to fewer success stories to report. We identify this as an important area of technology research and development. 1.5D implementations of the inverse scattering series attenuation algorithm (Araújo, 1994; Weglein et al., 1997) are currently being developed with land application particularly in mind (Hernandez and Innanen, 2014; Pan et al., 2014; Pan and Innanen, 2014). Amongst potential responses to the special problems of multiple removal on land, refinement of our use of prediction algorithm parameters holds significant promise. In this short note we discuss the role of the integration-limiting parameter  $\epsilon$  (as initially identified and applied by Coates and Weglein, 1996) within the algorithm, and investigate the possibility that optimum values of  $\epsilon$  should vary with offset-wavenumber. We show with a simple synthetic that a fixed constant  $\epsilon$  is responsible for large-dip artifacts in the prediction. These artifacts can be mitigated with post-prediction filtering, but we further demonstrate that a  $k_g$  dependent  $\epsilon$ , in addition to being a more elegant solution based on the origins of the artifacts, produces a cleaner result.

## Internal multiple prediction in 1.5D and ε-related artifacts

The inverse scattering series internal multiple attenuation algorithm is applied in 1.5D settings (pre-stack data over a layered medium) via the algorithm

$$PRED(k_g, \omega) = \int_{-\infty}^{\infty} dz \, e^{ik_z z} b_1(k_g, z) \int_{-\infty}^{z-\epsilon} dz' e^{-ik_z z'} b_1(k_g, z') \int_{z'+\epsilon}^{\infty} dz'' e^{ik_z z''} b_1(k_g, z'')$$

where  $k_z = 2 \left( \omega^2/c_0^2 - k_g^2 \right)^{1/2}$ . The quantity  $b_1$  is constructed directly from the data; this is discussed in greater detail below. Via nested integrals, the data are combined nonlinearly such that appropriate sub-events (Weglein et al., 1997) generate the correct phase and approximate amplitude of internal multiples. The limits of the integrals are altered by the choice of the search parameter  $\varepsilon$ . In Figure 1 we show a synthetic shot record (anticipating later results) in order to quickly illustrate the problem. A split-spread shot gather synthesized over a two interface acoustic model is illustrated in Figure 1a, and the raw internal multiple prediction constructed using the optimum fixed  $\varepsilon$  value derived from analysis of the zero-offset trace

(Hernandez, 2012) is illustrated in Figure 1b. The artifacts in question are the large-dip linear events intersecting the bottom axis of the prediction at roughly 1000m and 4000m, which correlate with the large-offset arms of the shallowest primary.

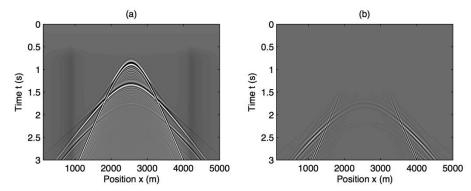


Figure 1. The issue at hand. (a) Input synthetic data taken over a two interface acoustic model; (b) raw prediction generated with fixed  $\varepsilon$ . Large-dip artifacts are visible intersecting the bottom of the panel at roughly 1000m and 4000m.

The correlation between the artifacts and primaries in the original data provides a clue as to their origin. The role of  $\epsilon$  is to limit the ability of the algorithm to classify nearby sub-events as satisfying the "lower-higher-lower" (LHL) criterion (Weglein et al., 2003). This criterion, applied to resolvable events, gives rise correctly to internal multiple estimates. However, a finite-length wavelet, internally to itself, has lobes, and the lobes of a single wavelet also obey a LHL relationship. If these are permitted to act as bona fide sub-events, artifacts coinciding with primaries are produced. The parameter  $\epsilon$  forces LHL to be applied only to large scale event combination. The fact that the artifacts in Figure 1b both match with primaries, and emerge at large dip, is suggestive that the  $\epsilon$  value is too small in application to the larger  $k_g$  values. Our scheme to manage these artifacts is illustrated in Figure 2.

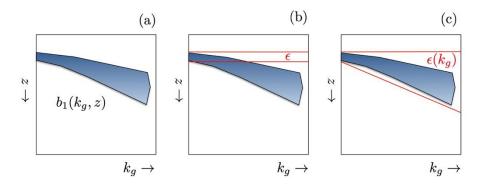


Figure 2. Artifact mitigation scheme. (a) Illustration of the input  $b_1(k_g, z)$ ; (b) integration-limiting parameter  $\varepsilon$  fixed at a size appropriate to  $k_g$ =0; (c) our response is to vary  $\varepsilon(k_g)$  to capture the "spread" of the subevent.

### **Numerical example**

To illustrate the potential benefits of this scheme, we create a synthetic data set (using the acoustic finite-difference package in the CREWES Matlab toolbox) as follows. A two- interface acoustic model with large impedance contrasts is chosen (Figure 3), and a split-spread shot record is modelled from it (Figure 4).

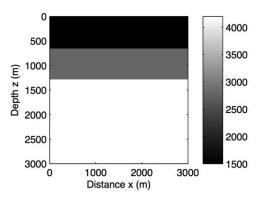


Figure 3. Acoustic model input to synthetic modelling code.

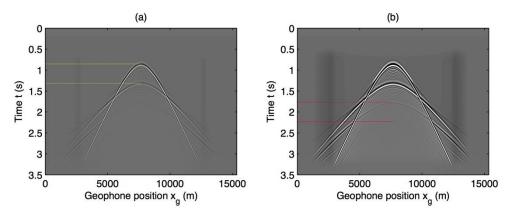


Figure 4. Synthetic data, large time/offset taper included. (a) Two reflected primaries are indicated with yellow lines; (b) with the clip lowered, two of the series of internal multiples are illustrated with red lines.

Next, we Fourier transform the data, re-sample, and scale, to form the input  $b_1(k_g,k_z)$ , in which  $k_z$  is the Fourier variable conjugate to pseudo-depth  $z=c_0t/2$ . This is inverse Fourier transformed over  $k_z$  to obtain the input quantity  $b_1(k_g,z)$ . The absolute values of  $b_1(k_g,z)$  are plotted in Figure 5. On the left edge of the panel  $(k_g=0)$  the two primaries can be seen intersecting the z axis at their proper pseudo-depths (i.e., the depths which an assumed velocity of  $c_0$  =1500m/s would place them). Moving to the right to growing values of  $k_g$ , the spreading of  $|b_1(k_g,z)|$  in z is notable.

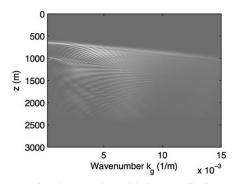


Figure 5. The input to the internal multiple prediction algorithm  $|b_1(k_g, z)|$ .

The input is then fed raw into a Matlab implementation of the internal multiple prediction algorithm with  $\epsilon$  initially fixed in units of time to 0.3s, which keeps the multiples (as analyzed in the zero-offset trace) separate, while accommodating the ringing wavelet that arises in the 2D acoustic modelling. The input data and the resulting prediction are illustrated in Figures 6a and b, which we discussed in the previous section.

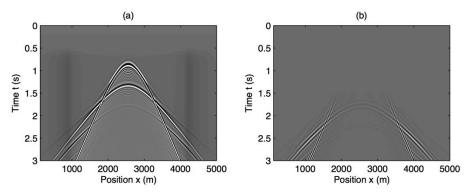


Figure 6. a) Input synthetic data, and (b) prediction with fixed  $\varepsilon$  optimized by analyzing the zero-offset trace.

# Wavenumber-dependent search parameter

Because the artifacts have a characteristically large dip, not shared by the multiples in the prediction, we can of course mitigate this problem by filtering out the offending  $k_g$  values, post-prediction. However, a cleaner result that keeps us tied to the actual origins of the artifacts is obtainable by varying  $\epsilon(k_g)$ . A linear  $\epsilon$  which interpolates between a minimum (1D or  $k_g = 0$ ) value  $\epsilon_{min}$ , and a maximum value  $\epsilon_{max}$  is chosen:

$$\epsilon(k_g) = \left(\frac{\epsilon_{max} - \epsilon_{min}}{k_{gmax}}\right) k_g + \epsilon_{min}.$$

In Figure 7, the prediction is plotted, using  $\varepsilon_{min}$  = 0.3s and  $\varepsilon_{max}$  = 2.0s. It achieves by-and-large the same result as the post-hoc filtering, but more cleanly, and in a manner which addresses the problem's origins.

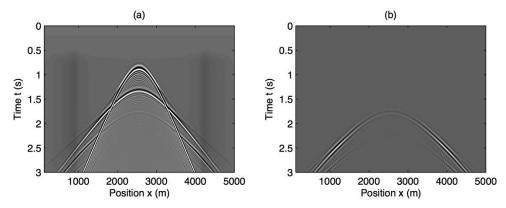


Figure 7. Prediction constructed using a linear  $\varepsilon(k_{\alpha})$ .

### **Conclusions**

We point out that large-dip artifacts noticeable in unfiltered 1.5D internal multiple pre- dictions can be mitigated by the employment of a  $k_g$ -dependent integration-limiting parameter  $\epsilon$ . The results are largely consistent with those obtainable by post-prediction filtering, but the  $\epsilon(k_g)$  approach is preferable in that it is tied to our interpretation of the origins of the artifacts. One potential benefit of adopting this approach to mitigation is that, in full 2D or even 3D versions of the algorithm, more complex artifacts, originating similarly, may arise, which simple post-hoc filtering cannot adequately fix, but which sub-event management via, for instance,  $\epsilon(k_g,k_s)$ , can. This is only a speculative statement at the moment.

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