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Nonstationary L_1 adaptive subtrraction with application to internal multiple attenuation

Scott Keating, Jian Sun, Pan Pan, and Kris Innanen
CREWES, Department of Geoscience, University of Calgary

Summary

Adaptive subtraction as applied to inverse scattering prediction of internal multiples is investigated. Specifically, the advantages of using an L_1, nonstationary adaptive subtraction over an L_2, stationary adaptive subtraction are investigated. Examples on both synthetic and physically modeled data show that the nonstationary L_1 adaptive subtraction is able to avoid unwanted matching to primaries, and is more capable of dealing with errors in the multiple prediction assumptions.

Introduction

Seismic experiments unavoidably generate multiple reflections, and these can often be of significant amplitudes as compared to the primary reflections measured. While there do exist specific techniques to gather meaningful information from multiple reflections, most seismic data processing and interpretation hinges on the assumption of primary only data. This causes methods of multiple removal to be of significant value in traditional processing and interpretation.

There exist computationally inexpensive methods for multiple removal that have been used effectively. These typically rely on some assumed difference between primary and multiple reflections. For example, predictive deconvolution relies on the assumption that multiples, and not primaries, display periodicity (Peacock and Treitel (1969)), whereas tau-p filtering methods assume moveout differences between primaries and multiples at any given arrival time (Foster and Mosher, 1992). While these methods enjoy great success in simple environments where their assumptions are valid, they become much less effective when confronted with more complex situations where their assumptions are challenged. An alternate approach to the multiple removal problem is wavefield prediction and subtraction. Rather than exploiting general differences between multiples and primaries, these methods specifically predict multiples, and subsequently remove them from the data. These methods include surface related multiple elimination (SRME) (Verschuur, 1992), and inverse scattering series prediction (Weglein et. al., 1997). While these methods are capable of dealing with complex geologies, there are assumptions and approximations that are in practice made while applying these methods. These lead to predictions which do not exactly match the multiples observed in the data, necessitating a matching between the measured data and prediction before they can be subtracted. This process of matching and removal is called adaptive subtraction.

In land seismic data, internal multiples tend to be the multiples of interest, as extra trips through a highly attenuative near surface tend to minimize the effect of free surface multiples. Computationally cheap methods of multiple removal are often impractical for internal multiples, making inverse scattering multiple prediction an appealing alternative. Inverse scattering multiple removal methods are being developed in a variety of domains, such as the wavenumber-pseudodepth domain (Pan, 2015), the tau-p domain (Sun and Innanen, 2014), and the space-time domain (Innanen, 2014). In this report, the advantages of a nonstationary application of the L_1 minimizing adaptive subtraction described by Guitton and Verschuur

(2004) over a more traditional stationary L_2 adaptive subtraction (Verschuur, 1992) are investigated, as applied to inverse scattering internal multiple predictions on both synthetic and physically modelled data.

Theory

Before the multiples generated by wavefield prediction methods can be subtracted from the data, it is necessary that the predicted wavefield is modified to better match the observed multiples. In adaptive subtraction, this matching is typically done by convolving the prediction with a filter. As we do not know the correct multiple prediction, the question of how to choose this filter becomes important in adaptive subtraction.

One of the simplest criteria we can choose is to select the filter which minimizes the L_2 norm (and thus energy) of the data after adaptive subtraction. In this formulation, the filter chosen will remove as much energy from the data as possible. The idea behind this criterion is that the data without multiples will be lower energy than any version of the data still containing multiples (Verschuur, 1992). Implicit in this criterion is the assumption that regardless of the filter we choose we will not be removing primary reflections. While this assumption is applicable in some situations, it fails when confronted with interference between primaries and multiples in the measured data. When primary-multiple overlap exists, the energy minimizing adaptive subtraction often removes both primary and multiple signal. Often in seismic data the primaries are larger in amplitude than the multiples, as the energy is proportional to the square of amplitude, these primaries often contain far more energy than the multiples. Consequently, removal of primary reflections is often far prioritized over multiple removal in an L_2 adaptive subtraction, potentially leading to poor removal of multiples and unwanted removal of primary energy.

An alternative to the L_2 minimizing criterion is L_1 norm minimization. The filter which minimizes the L_1 norm minimizes the amplitude of the seismic data after than subtraction instead of energy, its square. This has the result of greatly diminishing the weighting of high amplitude points as compared to the energy minimizing filter. This reduces the degree of unwanted matching to primary data.

Another way in which the filter being used can be improved is by moving from a stationary to a nonstationary filter. With a stationary filter, a single correction is applied at all locations in the data prior to subtraction. A nonstationary filter allows for this correction to vary with position and time. This is useful when the seismic data themselves exhibit nonstationarity, or when the validity of assumptions made in the wavefield prediction varies in space or time.

Examples

A synthetic shot record containing several internal multiples was generated using an acoustic finite difference model to test these adaptive subtractions. This synthetic shot record is shown in Figure 1. This shot record is generated using a velocity model with slightly dipping layers, but the inverse scattering multiple prediction is made based on a flat layer assumption. The advantages of using a nonstationary filter instead of a stationary one are highlighted in Figure 1, where the stationary adaptive subtraction fails badly at certain offsets, but the nonstationary adaptive subtraction performs well. On these synthetic data there is relatively little primary-multiple overlap, and so there is little difference between the result of an L_1 subtraction and an L_2 subtraction.

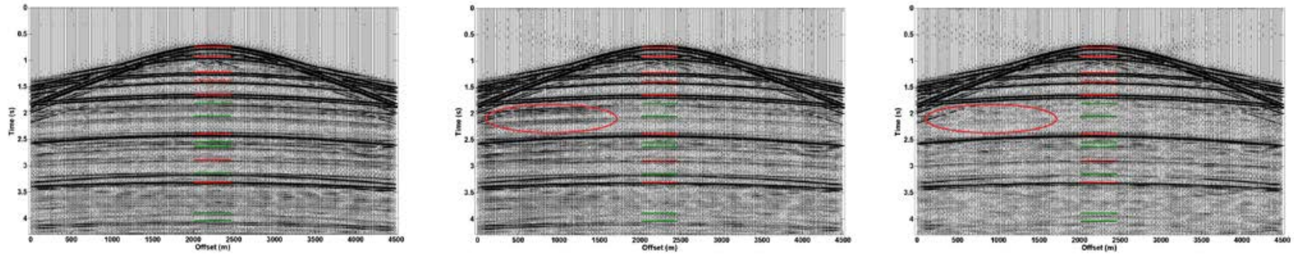

FIG. 1. Left: Synthetic shot record with slightly dipping layers. Red lines mark primaries, green mark multiples. Center: Shot record after stationary adaptive subtraction. Poor subtraction occurs at certain offsets. A problematic region is circled. Right: Shot record after nonstationary adaptive subtraction. Good subtraction occurs everywhere.

Adaptive subtraction was also tested on physical modelling data. The physical modeling was done on a scale model consisting of layers of water, polyvinyl chloride, Plexiglas and aluminum (Pan, 2015). Piezoelectric transducers were used for source and receivers. The 2D response of a single shot was measured, and an inverse scattering multiple prediction was generated, as shown in Figure 2. The result of a nonstationary, L_2 adaptive subtraction is shown in Figure 3. It is clear in this example that the L_2 subtraction is not performing well; the predicted multiples after applying the filter are significantly altered from the initial prediction in Figure 2, and the subtraction does a poor job of removing the multiples. By contrast, in Figure 4, the result of a nonstationary L_1 adaptive subtraction is shown. The L_1 subtraction does a better job of removing multiples, and comparison with Figure 2 shows that the filter is mostly performing local amplitude and phase corrections, rather than the unwanted matching to primaries seen in the L_2 adaptive subtraction.

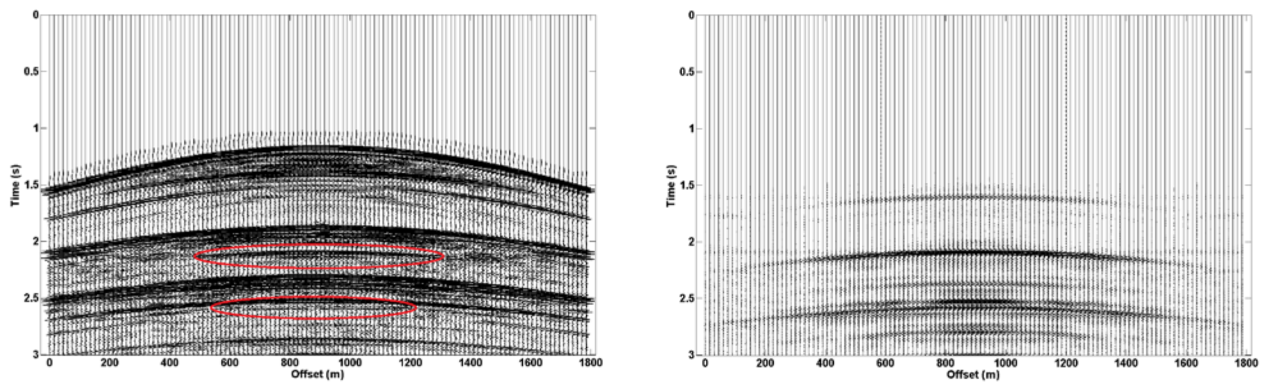

FIG. 2. Left: Physical modeling data with notable multiples circled in red. Right: Inverse scattering multiple prediction.

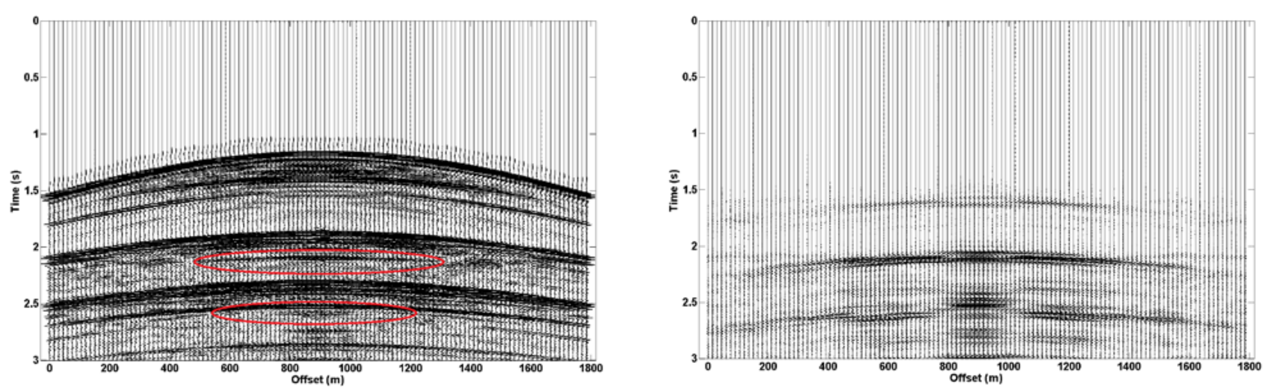

FIG. 3. Right: Physical modeling data after L_2 adaptive subtraction. Multiple removal is poor. New unwanted artifacts are present, especially after 2.5s. Left: Predicted multiples after application of energy minimizing filter. There is unwanted matching at about 2.5s

to a large primary. Overall, the prediction after the application of the filter is very different from the original prediction in Figure 2; the multiples are not being matched well.

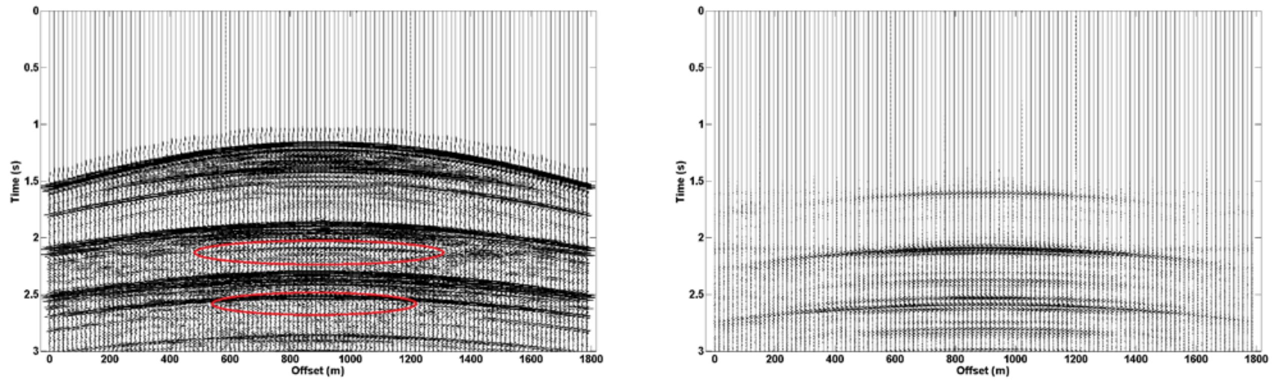

FIG. 4. Right: Physical modeling data after L_1 adaptive subtraction. Multiples are largely removed. Unwanted artifacts from Figure 3 are not present. Left: Predicted multiples after application of L_1 minimizing filter. Differences from Figure 2 are largely amplitude and phase corrections.

Conclusions

Moving to an L_1, nonstationary adaptive subtraction was found to offer significant improvements over L_2 and stationary adaptive subtractions. An L_1 minimization criterion helps to ensure that unwanted matching to primaries is avoided, and nonstationarity allows for coping with prediction errors that are not independent of position or time. The L_1 nonstationary adaptive subtraction was found to be effective on both synthetic and physically modeled data.

Acknowledgements

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