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Short Period Demultiple Using Iterative Second Order Multi-dimensional Predictive Deconvolution

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Summary

2D deconvolution is an attractive approach for short period multiple prediction as it does not require direct recording of the multiple generator and can model multiples relating to more than one multiple generator at a time. One drawback, however, relates to an inherent over-prediction of mixed side multiples as well as some shallow multiples, leading to an inconsistency in the amplitude of multiple predictions from one multiple order to the next. We present a modified form of predictive deconvolution that corrects for these errors by iteratively refining the data used for the gapped deconvolution solver. The resulting multiple prediction is consistent with the amplitude of multiples in the recorded data, reducing the necessity for adaptive subtraction. The algorithm may be applied in 2D or 3D, or alternatively with a receiver only side 3D implementation suited to towed streamer geometries. The effectiveness of the algorithm is demonstrated on synthetic data as well as on two towed streamer 3D seismic data examples acquired in the North Sea.

Introduction

Many surface related multiple attenuation algorithms model multiples by convolving recorded data with a primary estimate. Probably the best known of these approaches is SRME (Berkhout and Verschuur, 1997) where the primary estimate is initialised by the data itself. The multiple model from SRME is typically adaptively subtracted from the data, a process which corrects for inaccuracies in the multiple model relating to the source wavelet, cross-talk between multiples and missing or under sampled data. When the multiple generator has not been sufficiently recorded SRME can break down. In such cases, the primary estimate may be provided by a reflectivity image (Pica et al., 2005) or Green's function multiple modelling (Wang et al., 2011). Gapped deconvolution approaches such as tau-p deconvolution or 2D deconvolution (Biersteker, 2001) offer an alternative where information about the multiple generator is derived from the periodicity of multiples in the data itself.

Backus (1959) described a second order correction for 1D predictive deconvolution which improved the amplitude consistency of the multiple prediction. The approach has been adapted for the cases of SRME (Hugonnet, 2002) and Green's function multiple modelling (Cooper et al., 2015). We describe a combination of shallow and iterative second-order correction terms which overcome amplitude inconsistencies experienced by standard multi-dimensional deconvolution. In addition we describe a receiver side 3D implementation, working on each sailline of a towed streamer dataset independently. The method is validated on synthetic data and applied on two real datasets from the North Sea.

Methodology

The combined source and receiver 2D gapped deconvolution equations may be given by:

$$d_{ik} = p_{ik} + \sum_j g_{ij} * d_{jk} + \sum_j d_{ij} * g_{jk} \tag{1}$$

where input data, d, is predicted by a multi-channel convolution between the data and surface consistent prediction operator, g, with indices i, j, and k relating to spatial coordinates for the spatial summation as described in Biersteker (2001) plus primary, p. The surface consistent prediction operator is shared for source and receiver sides with an appropriate gap and active operator length to prevent prediction of the primaries. The linear equations may be solved using least squares inversion to find the prediction operator, following which a multiple estimate is made by convolving the prediction operator with the recorded data.

To explore the accuracy of the multiple prediction, we consider a subset of arrivals in the input data consisting of primaries followed by peg-leg multiples, $d^{(pl)}$, as illustrated in Figure 1a. We describe this dataset in terms of a primary, p, source only side multiples, $p\sum S^a$, receiver only side multiples, $p\sum R^b$, and mixed side multiples, $p\sum S^a \sum R^b$. Operators S and R relate to convolution operations (provided by multiplications in the frequency domain) by the multiple generator on source and receiver sides respectively, a and b relate to the multiple order on source and receiver sides respectively.

$$d^{(pl)} = p\left(1 + \sum_{a=1}^{\infty} S^a + \sum_{b=1}^{\infty} R^b + \sum_{a=1}^{\infty} S^a \sum_{b=1}^{\infty} R^b\right) \tag{2}$$

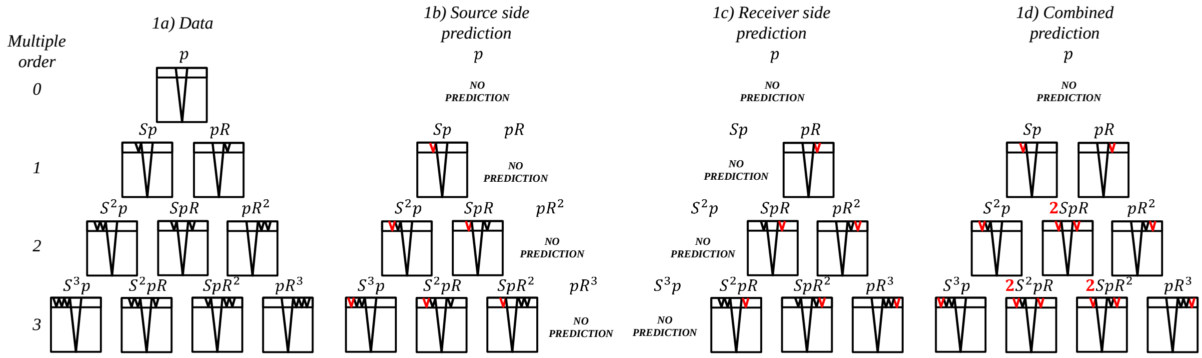

***Figure 1** Illustration of the double counting of mixed side multiples from multi-channel predictive deconvolution*

Including source and receiver side convolutions, the 2D deconvolution will produce:

$$d^{(pl)}S + d^{(pl)}R = p\left(\sum_{a=1}^{\infty} S^a + \sum_{a=1}^{\infty} S^a \sum_{b=1}^{\infty} R^b\right) + p\left(\sum_{b=1}^{\infty} R^b + \sum_{a=1}^{\infty} S^a \sum_{b=1}^{\infty} R^b\right) = p\left(\sum_{a=1}^{\infty} S^a + \sum_{b=1}^{\infty} R^b + 2\sum_{a=1}^{\infty} S^a \sum_{b=1}^{\infty} R^b\right) \quad (3)$$

While source only and receiver only side multiples have been correctly predicted, the mixed side multiples have been double counted. Figures 1b and 1c show the multiples predicted by the source and receiver side convolutions. Figure 1d shows the combined multiple estimate, highlighting the double prediction of the mixed side multiples.

To correct for the over prediction we propose to iteratively modify the data used for the convolutions using the prediction operator from the previous iteration. In the following equation, $g^{(n-1)}$ relates to the operator from the previous iteration and $g^{(n)}$ is a new operator we will find by least squares inversion. The factor of a half prevents over-prediction of the mixed side multiples.

$$d_{ik} = p_{ik} + \sum_j g_{ij}^{(n)} * d_{jk}^{(r)} + \sum_j d_{ij}^{(s)} * g_{jk}^{(n)}$$

where: $d_{ik}^{(r)} = d_{ik} - \frac{1}{2}\sum_j d_{ij} * g_{jk}^{(n-1)}$ and $d_{ik}^{(s)} = d_{ik} - \frac{1}{2}\sum_j g_{ij}^{(n-1)} * d_{jk}$. (4)

We now consider multiples that relate to a primary corresponding to an event represented by the prediction operator. Considering the case where the prediction operator predicts only waterbottom multiples, this would relate to arrivals that have only travelled in the water layer. We describe this sub-set of the data as a primary followed by receiver side multiples: $d^{(g)} = p\left(1 + \sum_{b=1}^{\infty} R^b\right)$. Applying our modified prediction scheme (4) for peg leg multiples, we find:

$$d^{(g)}(2R - R^2) = p\left(2\sum_{b=1}^{\infty} R^n - \sum_{b=2}^{\infty} R^n\right) = p\left(2R + \sum_{b=2}^{\infty} R^n\right). \quad (5)$$

Equation 5 shows that while multiple orders two and onwards have been predicted accurately, the first order multiple has been double counted. For this reason, we propose scaling the data in the interval relating to the multiple generator in Equation 5 by a half. This has equivalence to the approach proposed by for partial SRME by Hugonnet (2002). Thus, our final algorithm may be stated as follows:

$$d_{ik} = p_{ik} + \sum_j g_{ij}^{(n)} * \left(d_{jk}^{(r)} - \tfrac{1}{2}h_{jk}\right) + \sum_j \left(d_{ij}^{(s)} - \tfrac{1}{2}h_{ij}\right) * g_{jk}^{(n)} \quad (6)$$

where h is the input data muted to the time interval of the prediction operator.

The algorithm may be applied in two or more spatial dimensions where data sampling allows. A receiver-side 3D application may be used for towed streamer data where receiver side multiples are predicted using shot domain operators that are spatially consistent for all shots within a sailline. In this case, and by making equivalence between source and receiver side multiples, we may use equation: $d_{ik} = p_{ik} + 2\sum_j \left(d_{ij}^{(r)} - \frac{1}{2}h_{ij}\right) * g_{jk}^{(n)}$. De-aliasing of data in-between the streamers may be implemented with data interpolation, for example using NMO copy and spatial weighting.

The algorithm may be used to output the second order correction term in addition to the full multiple model which may be used for joint or cascaded adaptive subtraction.

Synthetic example

The synthetic example relates to a 3D dipping primary event at 2500 m depth and associated peg-leg multiples generated by a water bottom at 150 m depth, modelled on a towed streamer geometry. The synthetics were generated using 3D diffraction modelling with water velocity 1500 m/s and sediment velocity 3000 m/s. Figure 2a shows the input data consisting of a primary reflection followed by source and receiver side peg-leg multiples. Figures 2b and 2c show the multiple model and straight subtraction using conventional 3D deconvolution. Figures 2d and 2e show the multiple model and straight subtraction using the proposed approach. The filled wiggle traces highlight how the predicted first order multiple has strengthened and subsequent multiple orders have weakened using the proposed approach. The subtraction results show how the improved amplitude consistency of the proposed multiple model has resulted in less residual multiple.

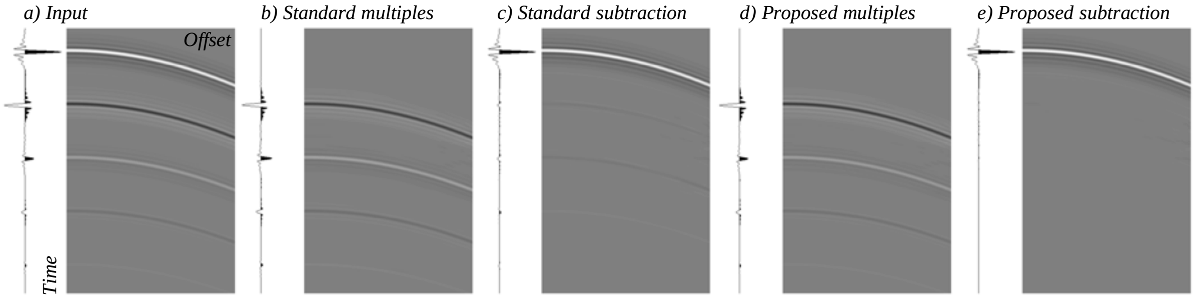

Figure 2 *Synthetic shotpoint gather comparing standard deconvolution and the proposed approach*

Real data examples

The first dataset is a North Sea variable depth towed streamer example using 10 streamers with 100 m separation. Pre-processing included source designature, receiver deghosting, and re-datuming to sea surface. Figure 3 displays demultiple results for a shot gather (top) and near offset channel (bottom). The shallow water environment produced many orders of peg-leg multiples creating a curtain of energy following each primary reflection. The demultiple result shows effective attenuation of multiples and highlights the amplitude consistency of the multiple model as no adaptive subtraction was used for this example. Figure 4 shows stacks of the data before and after demultiple which highlights the efficiency of the algorithm in attenuating multiples effectively in a single pass.

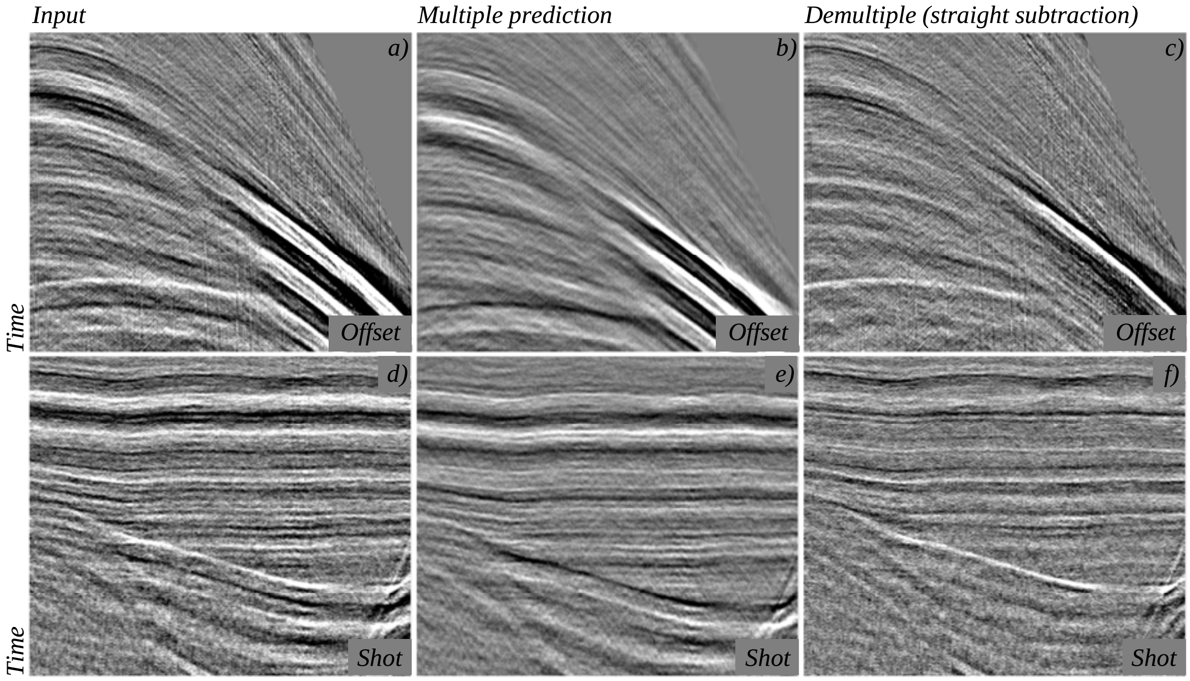

Figure 3 *Shot (a-c) and channel (d-f) displays for a straight subtraction of the proposed multiple prediction*

The second dataset is a split spread towed streamer example where a source vessel was positioned above the streamers (Vinje et al., 2017). The approach is effective at recording short offsets which provide improved imaging of the shallow section. Figure 5 shows a stack section of input data, multiple prediction, and after multiple subtraction. The demultiple result relates to a straight subtraction, highlighting the amplitude consistency of the method and reducing the need for adaption.

Conclusions

We have introduced a modified form of multi-channel predictive deconvolution using shallow and second order terms that compensate for the over counting of multiples. The approach iteratively estimates the prediction operator which is used to correct the data input to the deconvolution equations for the next iteration. The resulting multiple model has improved amplitude consistency for consecutive multiple orders, reducing the necessity for adaptive subtraction. Synthetic and real data examples highlight the efficiency of the approach in attenuating multiples in shallow water settings.

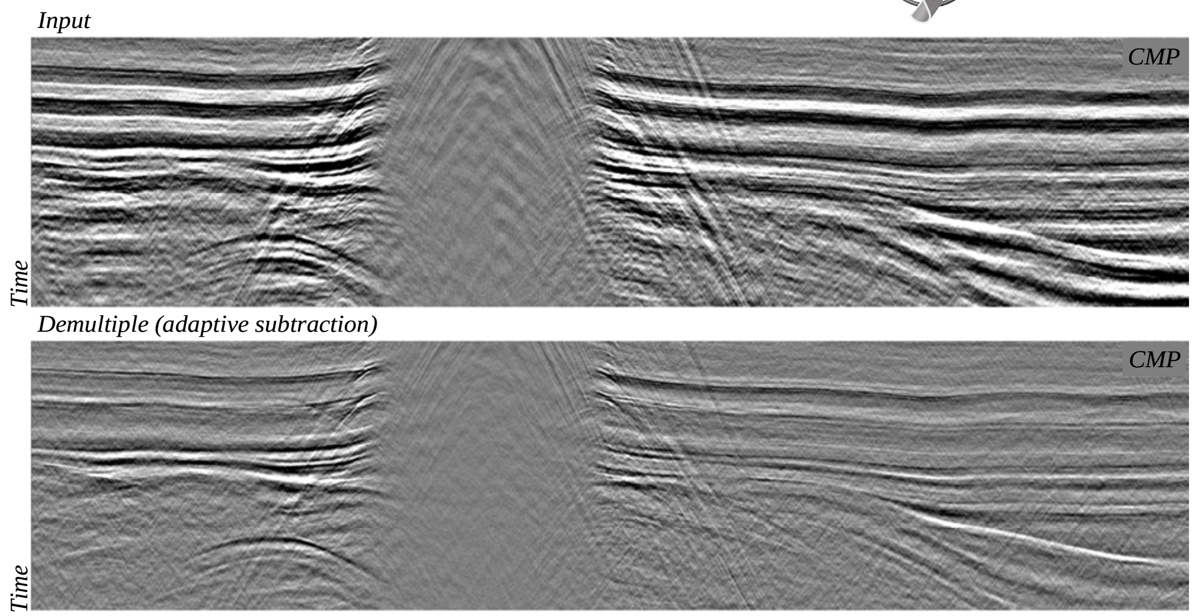

Figure 4 *Stacked section before and after demultiple using the proposed approach*

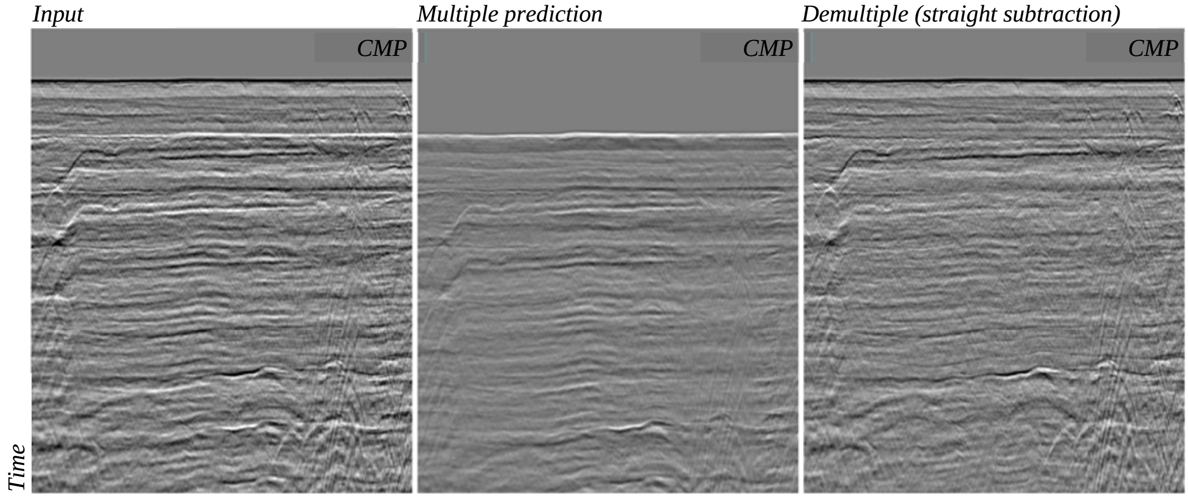

Figure 5 Split spread acquisition stacked section before and after demultiple using the proposed approach

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