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Recursive Model-based Water-layer Demultiple

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SUMMARY

In addition to other subsurface reflections, water-layer related multiples (WLRMs) involve at least one water-layer reflection between the free surface and the water bottom. In shallow water environments, WLRMs typically dominate other classes of multiple, and achieving effective attenuation of WLRMs is of significant interest. When combined with an appropriate adaptive subtraction, Model-based Water-layer Demultiple (MWD) has been found to be highly effective in attenuating WLRMs. In this paper we demonstrate a limitation of the conventional implementation of MWD, and propose an extension to the method to account for this limitation. This extension alleviates the dependence of a successful demultiple result on the adaptive subtraction. We demonstrate the effectiveness of our approach on simple 1D synthetics, and real-world 3D seismic data from towed-streamer acquisition in the North Sea.

Introduction

The success of surface-related multiple attenuation in shallow water environments is limited by an absence of near offsets and a lack of high quality water bottom primary reflections in the recorded data. Together with amplitude errors arising from cross-talk between multiples (Wang *et al.* 2014) these factors have been cited (Verschuur 2006) as causing the breakdown of Surface-Related Multiple Elimination (SRME) in shallow water. As an alternative, a traditional approach such as 1D predictive deconvolution in the τ-p domain can be used with some success, but this method is compromised by the assumption of a 1D multiple generator, and erroneous attenuation of primary reflections with a period similar to that of the multiple generator. Modern strategies include the use of multi-channel prediction operators to model water bottom primary reflections directly from Water-Layer Related Multiples (WLRMs) present in the recorded data (Biersteker 2001, Hargreaves 2006, Hung et al. 2010). This reduces the impact of the missing near offsets and the poorly recorded water bottom primary, but the data-derived prediction operators are susceptible to contamination by noise and other events unrelated to the WLRMs.

Wang et al. (2011) proposed a Model-based Water-Layer Demultiple (MWD) approach to estimate WLRMs based on a Green's function derived from a known water depth. With a sufficiently accurate Green's function, this method gives rise to a model predicting the timing of the multiples with a high degree of accuracy. In this paper we highlight inaccuracies in the relative amplitude of different orders of multiple predicted by MWD and propose a systematic method to correct this. We begin by demonstrating how the conventional MWD process can be modified to predict multiples with the correct amplitude, before illustrating this technique on both 1D synthetics and real-world seismic data.

Methodology

Consider the path, $\underline{\boldsymbol{m}}_{(i,j-i)}$, of a j^{th} order peg-leg WLRM of some event, R, where i and $(j-i)$ represent the number of water layer reflections on the source and receiver sides respectively. We regard a primary event as a zeroth order multiple (j=0). We denote by $\underline{\boldsymbol{s}}$ and $\underline{\boldsymbol{r}}$ the respective positions of the source and receiver corresponding to $\underline{\boldsymbol{m}}_{(i,j-i)}$. A schematic example is shown in Figure 1 for the case i=2, j=5. We denote by $\underline{\boldsymbol{D}}$ the recorded data, comprising primary data and all orders of WLRM. The j^{th} order multiples of R corresponding to the source-receiver pair, $(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}})$, are represented within $\underline{\boldsymbol{D}}$ by $\underline{\boldsymbol{M}}_j$, where

$$\underline{\boldsymbol{M}}_j = \sum_{i=0}^{j} \underline{\boldsymbol{m}}_{(i,j-i)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}}). \qquad (1)$$

A conventional MWD process (Wang et al. 2011) simultaneously predicts all orders of WLRM by convolving the recorded data, $\underline{\boldsymbol{D}}$, with a modelled water layer Green's function, $\underline{\boldsymbol{g}}(\underline{\boldsymbol{a}},\underline{\boldsymbol{b}})$, between two surface locations, $\underline{\boldsymbol{a}}$ and $\underline{\boldsymbol{b}}$. Modelling is carried out independently for source-side and receiver-side Green's functions. For illustration, we consider here each order of multiple in isolation, and examine how the model for each order is obtained. For $j \geq 1$, conventional MWD models j^{th} order multiples by convolving the $(j-1)^{th}$ order multiples in the recorded data with source-side or receiver-side Green's functions, so that the modelled j^{th} order multiple is described by $\underline{\boldsymbol{Q}}_j$, where

$$\begin{aligned}\underline{\boldsymbol{Q}}_j &= \sum_{i=0}^{j-1}\left(\underline{\boldsymbol{g}}(\underline{\boldsymbol{s}},\underline{\boldsymbol{s}}') \otimes \underline{\boldsymbol{m}}_{(i,j-i-1)}(\underline{\boldsymbol{s}}',\underline{\boldsymbol{r}}) + \underline{\boldsymbol{m}}_{(i,j-i-1)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}}') \otimes \underline{\boldsymbol{g}}(\underline{\boldsymbol{r}}',\underline{\boldsymbol{r}})\right) \\ &= \sum_{i=0}^{j-1}\left(\underline{\boldsymbol{m}}_{(i+1,j-i-1)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}}) + \underline{\boldsymbol{m}}_{(i,j-i)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}})\right) \\ &= \sum_{i=0}^{j} \underline{\boldsymbol{m}}_{(i,j-i)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}}) + \sum_{i=1}^{j-1} \underline{\boldsymbol{m}}_{(i,j-i)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}}) = \underline{\boldsymbol{M}}_j + \sum_{i=1}^{j-1} \underline{\boldsymbol{m}}_{(i,j-i)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}}). \qquad (2)\end{aligned}$$

Here, $\underline{\boldsymbol{s}}$**'** and $\underline{\boldsymbol{r}}$**'** (Figure 1) are source and receiver positions intermediate to $\underline{\boldsymbol{s}}$ and $\underline{\boldsymbol{r}}$, taken to be the surface locations of the apexes of the multiple contribution gathers (MCGs) associated with the convolutions on the source and receiver sides respectively (Verschuur 2006, Wang et al. 2011).

The timings of the predicted multiples are fully consistent with the recorded data, but their amplitudes are not. The final term in (2) represents the amplitude error in the modelled multiple from the recorded multiple. In the case of first order multiples (j=1), this error term is zero and the multiples are predicted with the correct amplitude. However, the amplitudes of higher order multiples are over-predicted. The aim of the present work is to correct for this by developing an auxiliary MWD model which itself comprises only the error term in (2).

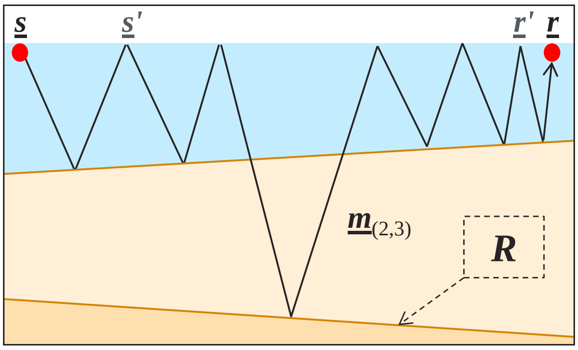

Figure 1 *Schematic of a 5^{th} order WLRM.*

Consider a multiple model constructed in the following way. Initially, we generate a conventional MWD model from the recorded data, but for receiver-side Green's functions only. Suppose the *output* from this modelling process is then used as the *input* data to a second conventional MWD modelling process, this time for source-side Green's functions only. In this way, for $j \geq 2$, the j^{th} order multiples in the resulting model are obtained by convolving $(j\text{-}2)^{\text{th}}$ order multiples in the data with Green's functions on both the source and receiver sides. These j^{th} order multiples are described by $\underline{\boldsymbol{E}}_j$, where

$$\underline{\boldsymbol{E}}_j = \sum_{i=0}^{j-2} \underline{\boldsymbol{g}}(\underline{\boldsymbol{s}},\underline{\boldsymbol{s}}') \otimes \underline{\boldsymbol{m}}_{(i,j-i-2)}(\underline{\boldsymbol{s}}',\underline{\boldsymbol{r}}') \otimes \underline{\boldsymbol{g}}(\underline{\boldsymbol{r}}',\underline{\boldsymbol{r}}) = \sum_{i=0}^{j-2} \underline{\boldsymbol{m}}_{(i+1,j-i-1)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}})$$
$$= \sum_{i=1}^{j-1} \underline{\boldsymbol{m}}_{(i,j-i)}(\underline{\boldsymbol{s}},\underline{\boldsymbol{r}}). \tag{3}$$

Thus, $\underline{\boldsymbol{E}}_j$ is precisely the error term found in (2); its role in MWD is similar to that played by the corrective term (Backus 1959) used by Hugonnet (2002) for SRME. Corrected multiple amplitudes for any order can then be recovered by direct subtraction of $\underline{\boldsymbol{E}}_j$ from $\underline{\boldsymbol{Q}}_j$. This describes a workflow in which an amplitude-consistent MWD model can be obtained by several applications of conventional MWD modelling processes. We refer to this procedure as Recursive MWD (RMWD).

Examples

The recursive MWD principle can be illustrated intuitively with a 1D example, as shown in the synthetic traces labelled (i) to (vi) in Figure 2. The amplitude of the Green's function here is $G<0$, the sign incorporating the change in polarity due to the reflection at the free surface. Trace (i) represents the recorded data, with a water bottom of amplitude $-G$, and a deeper primary event of amplitude $P>0$. The first three orders of WLRM of the primary event are shown, with amplitudes $2GP$, $3G^2P$ and $4G^3P$. The amplitude of a j^{th} order multiple is $(j+1)G^jP$. For simplicity of illustration, multiples of the water bottom itself are ignored. Trace (ii) shows the multiples predicted by conventional MWD. This predicts the timing of the multiples correctly, but with amplitudes equal to $2jG^jP$ for a j^{th} order multiple. The amplitude of the first order multiple (j=1) is correctly predicted, but higher orders are over-predicted. Trace (iii) shows the auxiliary MWD model, as described in (3). This model predicts amplitudes equal to $(j\text{-}1)G^jP$ for a j^{th} order multiple. Trace (iv) shows the RMWD model, the result of subtracting (iii) from (ii). Subtractions of the MWD and RMWD models from the recorded data are shown respectively in traces (v) and (vi). More generally, the RMWD model is seen to be amplitude-consistent with the recorded data for all orders of WLRM, by observing that the coefficients $2j$ and *(j-1)* in the expressions given above for the conventional and auxiliary models respectively, yield *(j+1)* upon subtraction, the coefficient given above for a j^{th} order WLRM in the recorded data.

A second example, on real data, is shown in Figure 3. These are near-offset common channel displays for a 3D shallow-water North Sea dataset, after pre-conditioning to remove the source signature, source ghost and receiver ghost. The recorded data before demultiple is shown in Figure 3a, where a primary event and several orders of WLRM are observed. Figures 3b and 3c show the conventional and recursive models respectively. The results of direct subtraction of the MWD and RMWD models are then shown in Figures 3d and 3e respectively. The boxes on Figures 3a to 3e highlight areas where

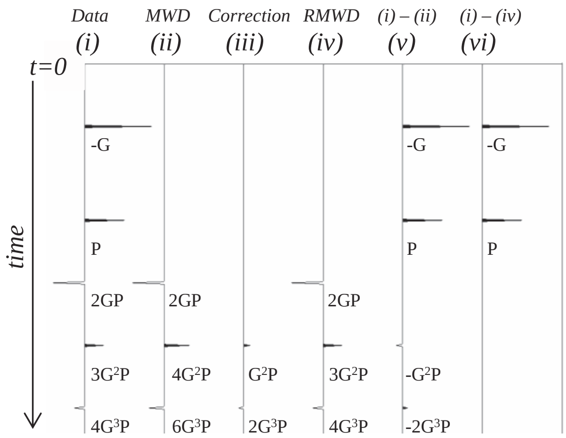

Figure 2 *RMWD for 1D synthetic.*

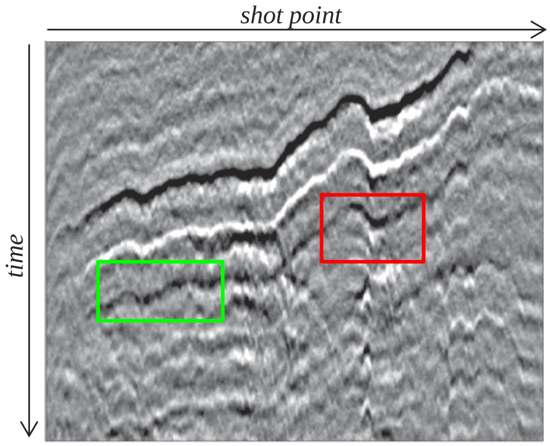

Figure 3a *RMWD: recorded data with multiples.*

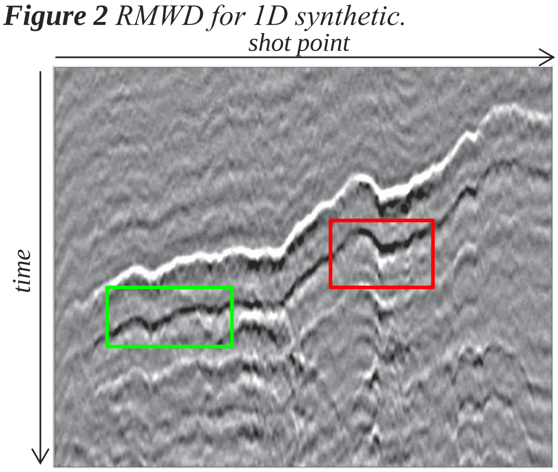

Figure 3b *RMWD: conventional multiple model.*

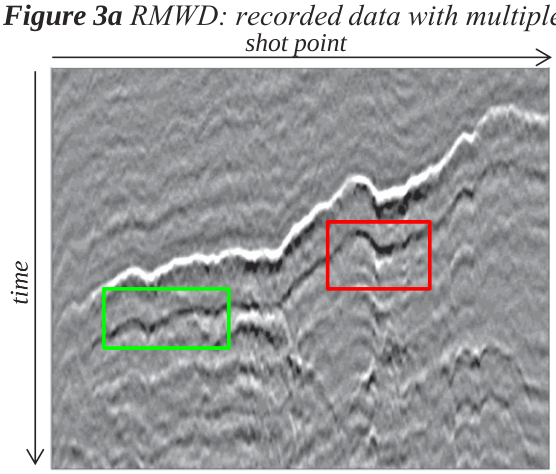

Figure 3c *RMWD: recursive multiple model.*

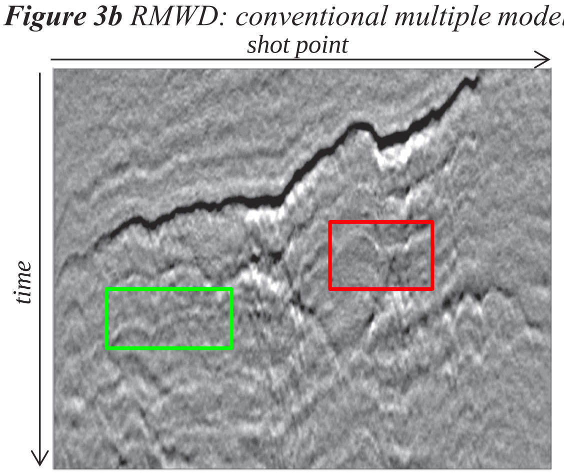

Figure 3d *RMWD: direct subtraction with conventional model.*

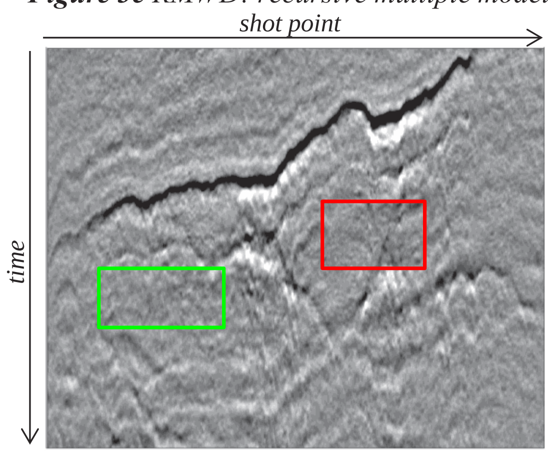

Figure 3e *RMWD: direct subtraction with recursive model.*

Figure 3 *A comparison of conventional and recursive MWD modelling, on a near-offset channel.*

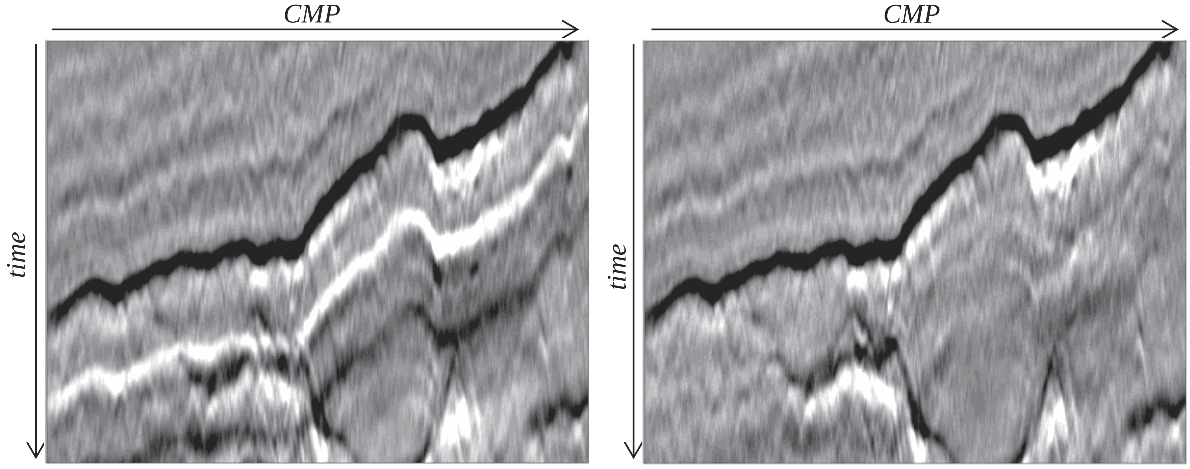

Figure 4 *Stack sections before (left) and after (right) direct subtraction with the RMWD model.*

the benefits of RMWD are most obvious. Results on CMP stacks are shown in Figure 4, before and after direct subtraction with the RMWD model, illustrating effective attenuation of WLRMs.

Conclusions

We have demonstrated an extension to conventional MWD which can be used to obtain a multiple model predicting the correct timing and amplitudes for all orders of WLRM. RMWD is described here via a workflow comprising repeated application of conventional MWD processes. The method permits a direct subtraction of the multiple model from the recorded data. Alternatively, it may be used within the context of an adaptive subtraction, in which the amplitude consistency of the recursive model avoids the need for aggressive adaptations that might otherwise be necessary with a conventional model. This reduces the likelihood that multiple energy in the model is erroneously adapted to primary energy in the recorded data.

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