

## A new multiple subtraction method using the attributes of predicted multiples

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### Summary

Despite the development of excellent techniques for predicting multiples such as convolution based or wavefield extrapolation based approaches, subtracting multiples in the data using the predicted multiples still remains as a challenge. The difficulty stems from the fact that many existing techniques try to match the predicted multiples to the multiples in the data by either adaptation or pattern matching. Because the prediction techniques mentioned above change the waveform of the predicted multiples, it will be very difficult to perfectly match the waveform of the predicted multiples to that of the multiples in the data. We report a new technique for subtracting the multiples using the attributes of the predicted multiples to determine the multiples in the data without any matching process. We illustrate the technique using a synthetic data set and show 3-D field data examples.

### Introduction

A substantial progress has been made for predicting surface-related multiples in the marine seismic data. There are two approaches for predicting multiples: convolution based prediction (e.g., Verschuur et. al., 1992) and wavefield extrapolation based prediction (Pica et. al, 2006). Comparison of these two approaches was well summarized by Matsen and Xia (2007). Both prediction methods mentioned above, although they can accurately predict the timing of the multiples, alter the waveform of the multiples. Convolution based approaches change the waveform by doubling the source wavelet spectrum in the frequency domain. In addition, interpolated traces to generate missing source-receiver pairs at the bounce points under the water surface may not have the same waveform of the missing traces. Wavefield extrapolation based approaches also change the waveforms unless one uses a perfect reflectivity model, which is impractical to obtain. Because of these waveform changes, subtracting multiples in the data using the predicted multiples is still a challenging task.

One common approach for subtracting the multiples using the predicted multiples is adaptive subtraction (Verschuur et. al., 1992). Adaptive subtraction tries to match the waveform of the predicted multiples to that in the data in both amplitude and phase in a window. If the window is small enough to include only multiples, the window may not be able to provide enough statistics to design a reliable filter. On the other hand, if the window is large, it may contain primaries and other noise to limit the adaptation process. Another approach is based on pattern matching

(Spitz, 1999). One designs a prediction error filter (PEF) for the primary by deconvolving the PEF of the data with that of the predicted multiples. Comparison of adaptive subtraction versus pattern matching is well documented by Abma et. al. (2005). They reported that a pattern matching technique tends to leave much residual multiple energy and to weaken the primaries where the predicted multiples overlapped the primaries.

We report a new approach using the attributes of the predicted multiples; namely, dip and average absolute value (AAV) along the dip. Instead of subtracting adapted or matched multiples, we subtract multiples directly estimated from the data using the dip and AAV of the predicted multiples. This approach avoids the matching process which may have been the main source of the shortcoming of previous approaches.

### Method

Figure 1 shows a flow diagram of the new method using the dip and AAV of the events in the data and in the predicted multiples. It consists of two steps. In the first step, we determine whether a given sample in the data belongs to a primary or a multiple. In the second step, we estimate the multiples in the data and subtract them from the data.

We use dip scan to determine the dip of the events in the data that contains primaries, multiples and other noises and the dip of the events in the predicted multiples. Next, the dip of the events in the data is compared with the dip of the events in the predicted multiples to separate the dip of the primaries. If the dip at a sample point in the data is sufficiently different from the dip at the same sample location in the predicted multiples, we consider the sample in the data as a primary. On the other hand, if they are similar, we regard the sample in the data as a multiple. In addition, we use AAV as another criterion to distinguish the primaries from the multiples particularly when the dips are similar. Because of spurious noises in the predicted multiples, the dip at a sample point in the predicted multiples can be similar to that of the sample at the same location in the data, but the AAV along the dip in the predicted multiples should be much smaller than the AAV along the same dip in the data. In such cases, we regard the sample as a primary.

In the second step, assuming the waveform does not change much over a few traces, we estimate the primaries by averaging over a few traces along the dip. We then subtract

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the estimated primaries from the data to obtain a new data set that contains all the multiples and some residual primaries that were not properly accounted for in the previous estimation step. Using the dip of the events in the predicted multiples, we estimate or reconstruct the multiples from the new data set by averaging over a few traces along the dip of the multiples. These estimated multiples are subtracted from the data. Reconstructing the multiples using the data set from which most primaries are removed allows for more reliable estimation of the multiples in the data.

Note that, instead of generating a filter that will try to match the predicted multiples to the multiples in the data, we directly determine the multiples in the data using the dip of the predicted multiples. In other words, we use the predicted multiples only to determine the dip of the multiples in the data, thereby avoiding a step of matching the waveform of the predicted multiples to that of the multiples in the data.

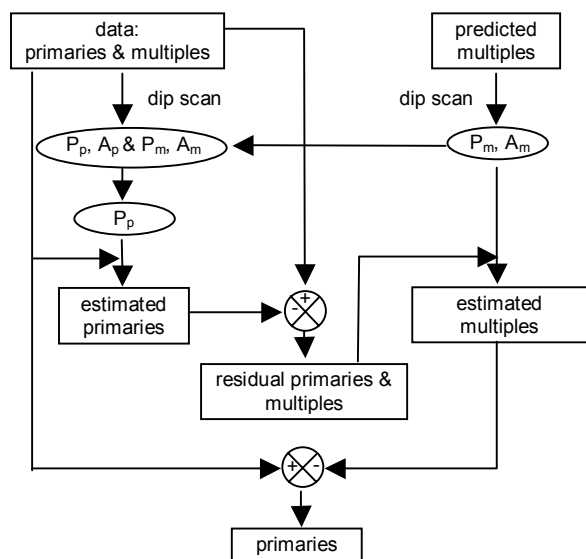


Figure 1. A flow diagram. P denotes the dip, and A denotes AAV. The subscripts p and m correspond to the primary and multiple, respectively.

Figure 2a shows a common offset synthetic data set that contains two flat primary events and one primary diffraction indicated by p and black arrows and their multiples. Figure 2b displays the predicted multiples using wavefield extrapolation. Basically, we added a round trip to each depth in the migrated section (not shown.) Note that the waveform of the predicted multiples is different from that of the data. By comparing the dip and AAV of the event in the data and those of the corresponding event

in the predicted multiples, we identify the primaries and their dip. We estimate the primaries by averaging over a few traces along the dip in the data and subtract them from the data, resulting in a new data set that mostly contains the multiples in the data. We use this data set to determine the multiples by averaging over a few traces along the dip of the multiples. Using the data set that mostly contains the multiples provides an advantage over using the original data set for determining the multiples. Because that the original data include the primaries or other noises, averaging over a few traces along a multiple dip can be affected by the primaries or other noises. Figure 2c shows the estimated multiples that will be subtracted from the data. Note that the waveform of the estimated multiples is the same as the waveform of the multiples in the data. The white arrows in figure 2 indicate (a) the multiple in the data, (b) the predicted multiple, and (c) the reconstructed multiple.

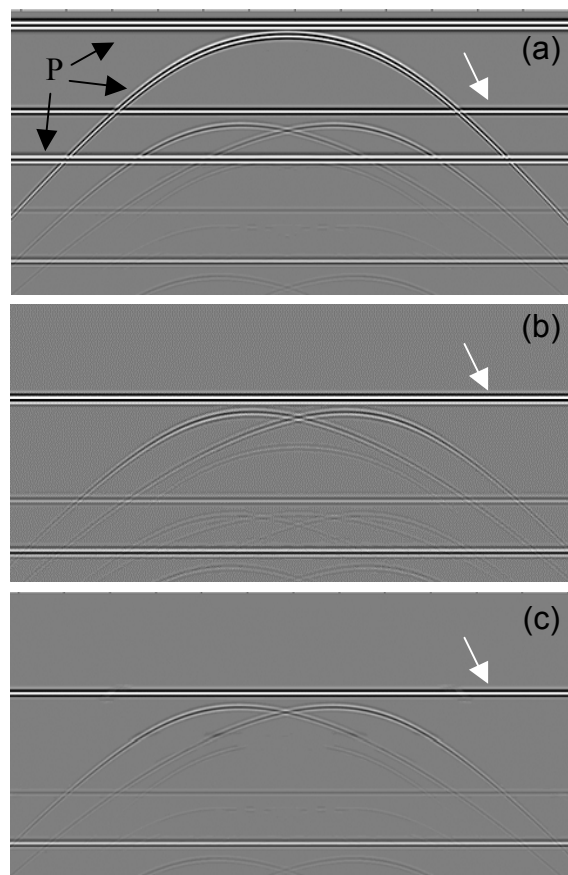


Figure 2. (a) A common offset section, (b) the predicted multiples, and (c) the reconstructed multiples.

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Shown in figure 3a is the result of subtracting the estimated multiples from the data. Note that all the multiples are subtracted properly. Figure 3b displays the result of adaptive subtraction. The flat primary where a diffracted multiple coincides with the primary in the data is distorted. Because the waveform of the predicted multiples and the waveform of the data where the primary and the diffracted multiple are overlapped are different from each other, adaptation can not be made perfectly to fit only the multiples in the data. In addition, a noticeable amount of multiple energy is left after adaptive subtraction (indicated by a white arrow.)

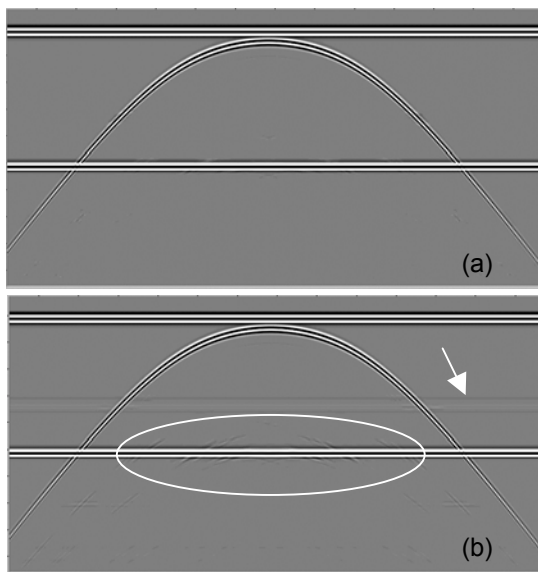


Figure 3. (a) Subtraction using the attributes of the predicted multiples, and (b) conventional adaptive subtraction. Note the residual multiples around the primary in the ellipse and indicated by a white arrow.

### Field data examples

Shown in figure 4a is a common offset section of an inline from a marine 3-D survey. The data were acquired using six streamers of length 9 km and with a cable spacing of 160 m in the deep water Gulf of Mexico. Because of severe feathering, each shot gather had to be regularized on a uniform grid with an inline spacing of 12.5 m and a crossline spacing of 80 m. A preliminary depth-migrated cube was used as a reflectivity model and the corresponding velocity model was used as a velocity model for wavefield extrapolation to predict the multiples. To prevent wraparound noises, we extended the computation

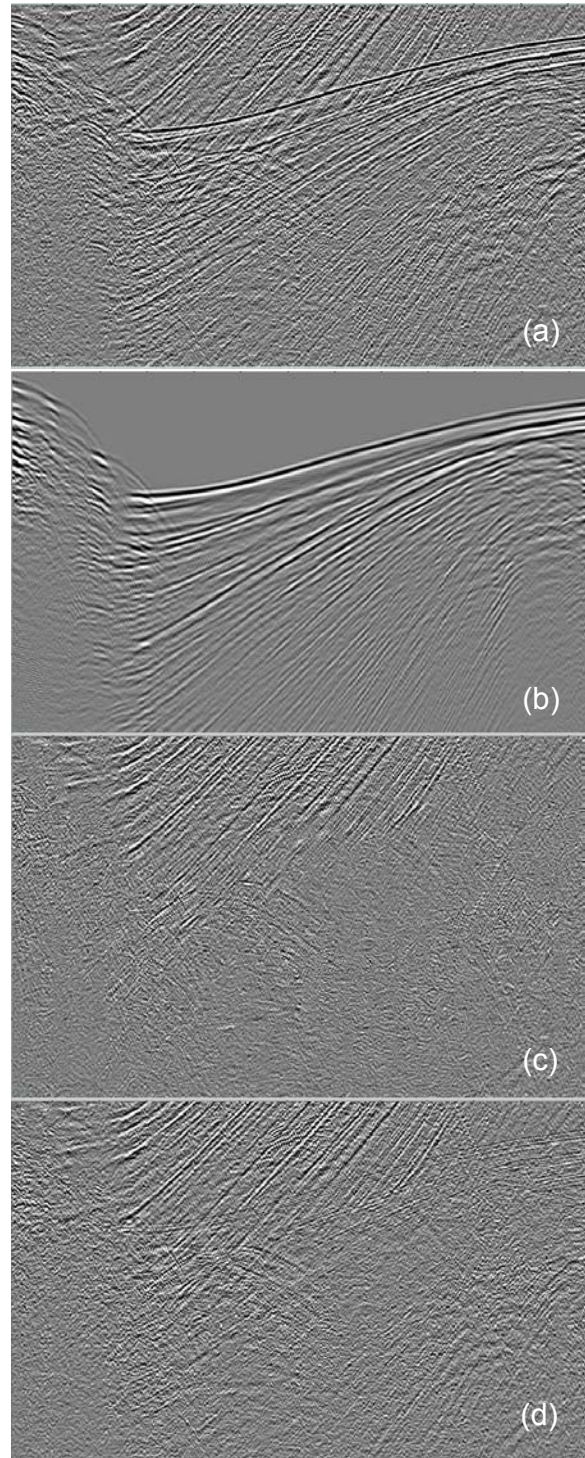


Figure 4. (a) Input, (b) predicted multiples, (c) attribute based subtraction, and (d) adaptive subtraction

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grid. The nominal distance of the computation grid in the crossline direction was 4 km. Because of severe feathering, some shots used a computation grid wider than 8 km in the crossline direction. We also padded about 6 km in the inline direction to avoid wraparound noises in the inline direction. Because the dip of the primaries is more different from the dip of multiples in the common offset domain than in the common shot domain, we applied the method in the common offset domain. Figure 4b shows the predicted multiples by extrapolating the shot gather to a depth of 3,000 m, which is deeper than the deepest top of the salt. This depth insures that WFE can predict both source and receiver side multiples bounded by the water surface and any reflectors down to the depth of 3,000 m. Note that the location of predicted multiples is precise, but the waveform of the predicted multiples is quite different from the waveform of the multiples in the data.

Figure 4c shows the result after subtracting the multiples using the new method. Note that the first order water bottom multiples and their peg legs are well suppressed. After subtracting the multiples, many steeply dipping primary events, which were masked by high amplitude multiples, are well retained. For comparison, we used an adaptive subtraction method and displayed in figure 4d. It was somewhat mild subtraction to preserve the primaries. As a result, a noticeable amount of multiple energy was left. Many steeply dipping primary events are still masked by residual multiples. If we tighten the adaptation parameters, we can subtract more multiples but at the cost of removing some primaries as well.

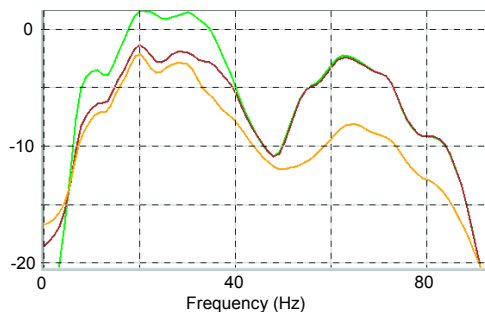


Figure 5. Amplitude spectra of the data shown in figure 4.

Shown in figure 5 are the spectra of the data shown in figure 4. The green curve shows the spectrum of the input data, the red curve shows the spectrum of the adaptive subtraction, and the brown curve shows the spectrum of the attribute-based subtraction. The notch in the input spectrum is due to towing the streamer at a depth of 18 m to retain the low frequency components of the data. These

spectra illustrate the performance of the two subtraction techniques. The adaptive subtraction method failed to match the predicted multiples to the multiples in the data in the high frequency range. Basically, there was no subtraction of high frequency components. On the other hand, the attribute-based subtraction worked well on all frequency components.

### Conclusions

Adaptive subtraction approaches have been a main tool for subtracting the predicted multiples from the data. However, matching can be either too aggressive or too mild. When it is too aggressive, the multiples can be eliminated, but many primaries are also partially removed. On the other hand, when matching is too mild, most primaries are preserved, but much of the multiple energy also remains.

A new method using the attributes of the data and predicted multiples avoids matching of the predicted multiples to the multiples in the data. Instead, it uses the dip and AAV at each sample in the data and in the predicted multiples to differentiate the primaries from the multiples. Once it is identified as a primary, the primary is estimated as an average of the samples along the dip over a few traces. These estimated primaries are subtracted from the data to make a new data set, from which we estimate the multiples by summing over a few traces along the dip of the multiples. The new method works well for most multiples except when a primary and a multiple overlap each other with the same dip and a similar AAV. For example, a flat primary and the apex of a diffracted multiples can overlap with a flat dip. In such cases, one may determine the dip by scanning over a large number of traces such that the AAV of the primary will be much higher than that of the diffracted multiples.

Tests on field data show that the new method can remove the multiples while preserving the primaries better than conventional adaptive subtraction methods.

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**EDITED REFERENCES**

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