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Subtraction of surface-related multiples: adaptive subtraction vs. pattern recognition

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ABSTRACT

Two multiple subtraction techniques are tested on a 2D synthetic dataset. The first technique is adaptive subtraction, where the signal is assumed to have minimum energy. The second technique is pattern recognition, where the signal and noise are assumed to have different multivariate spectra. Overall, the pattern based technique leads to a better subtraction of the multiples.

INTRODUCTION

In complex geology, multiples and primaries can be accurately separated by estimating a model of the multiples and subtracting it from the data (Verschuur et al., 1992). The subtraction of a given model is usually made by assuming that the signal (the primaries) has minimum energy. As exemplified by numerous authors (e.g., Spitz (1999); Kelamis et al. (2002); Lu (2003); Guo (2003); Guitton and Verschuur (2004)), the minimum energy assumption might not hold and other norms or subtraction techniques might be needed.

In Guitton (2003a), I demonstrated on a field data example that the pattern recognition technique presented in Guitton (2003b) gives the best multiple attenuation result for complex geology, thus providing an alternative to the popular adaptive subtraction method. In addition, I showed that 3D prediction error filters (estimated in the time, shot, offset domain) were more effective in characterizing the multivariate spectra of the noise and data than a series of 2D filters (time, offset) (Guitton, 2003a, 2004).

In this paper, I investigate both the adaptive subtraction technique with the ℓ^2 norm and the pattern-based method for a 2D synthetic data example. This example is perfectly suited for the adaptive subtraction since all the recorded events are propagating in the inline direction. In this comparison, I show that the pattern-based method performs generally better than the adaptive subtraction technique. However, where the noise and signal have similar patterns, I demonstrate that the pattern-based technique damages some primary reflections. This problem is mainly caused by the Spitz approximation which only provides an accurate signal model where the noise and signal are uncorrelated.

In the next section I briefly present the two subtraction techniques and the parameters

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used for the modeling of the multiples. Then I show the multiple attenuation results on a 2D synthetic model provided by BP.

SUBTRACTION OF MULTIPLES

Both adaptive subtraction and pattern recognition assume that a model is known. For this paper I use the method described by Verschuur et al. (1992) to compute the multiple model. In the sections below I describe how the two methods use the data and the multiple model to produce an estimate of only the signal.

Adaptive subtraction

Given a model of the multiple **M** and the data **d**, a bank of non-stationary filters **f** is estimated such that

$$g(\mathbf{f}) = \|\mathbf{Mf} - \mathbf{d}\|^2 + \epsilon^2 \|\mathbf{Rf}\|^2 \qquad (1)$$

is minimum (Rickett et al., 2001). In equation (1), **R** is the Helix derivative (Claerbout, 1998) that smooths the filter coefficients across micro-patches (Crawley, 2000) and ϵ a trade-off parameter between data fitting and smoothing. The filters have two dimensions. In the following results, the filters are 20×3 and the patch size is 44×20 (the first number corresponds to the time axis and the second number corresponds to the offset axis). Once the filters are estimated, the signal becomes

$$\hat{\mathbf{s}} = \mathbf{Mf} - \mathbf{d}. \qquad (2)$$

The subtraction is done one shot gather at a time.

Pattern recognition

As shown in (Guitton, 2003b), the estimated signal is given by:

$$\hat{\mathbf{s}} = (\mathbf{N}'\mathbf{KN} + \epsilon^2 \mathbf{S}'\mathbf{KS})^{-1} \mathbf{N}'\mathbf{KNd}, \qquad (3)$$

where **N** and **S** are the noise and signal prediction error filters (PEFs), respectively, ϵ a trade-off parameter and **K** a masking operator. The noise PEFs are estimated from the noise model. The signal PEFs are estimated with the Spitz approximation (Guitton, 2004). As we shall see later, the Spitz approximation works very well when the noise and signal are uncorrelated. 3D filters are estimated since they lead to the best multiple attenuation results (Guitton, 2003a, 2004).

For the following results, the filters size is $15 \times 3 \times 3$ (the last number corresponds to the shot axis) and the patch size is $16 \times 8 \times 5$. These numbers are identical for both noise and signal filters. With 3D filters, because of memory limitations, we cannot estimate the signal for a complete 2D line on one computer only. Therefore, we segment the 2D line into macro-patches of 50 successive shots. There is an overlap of 5 shots between adjacent macro-patches. Each macro-patch is processed on one node before being merged into the final file.

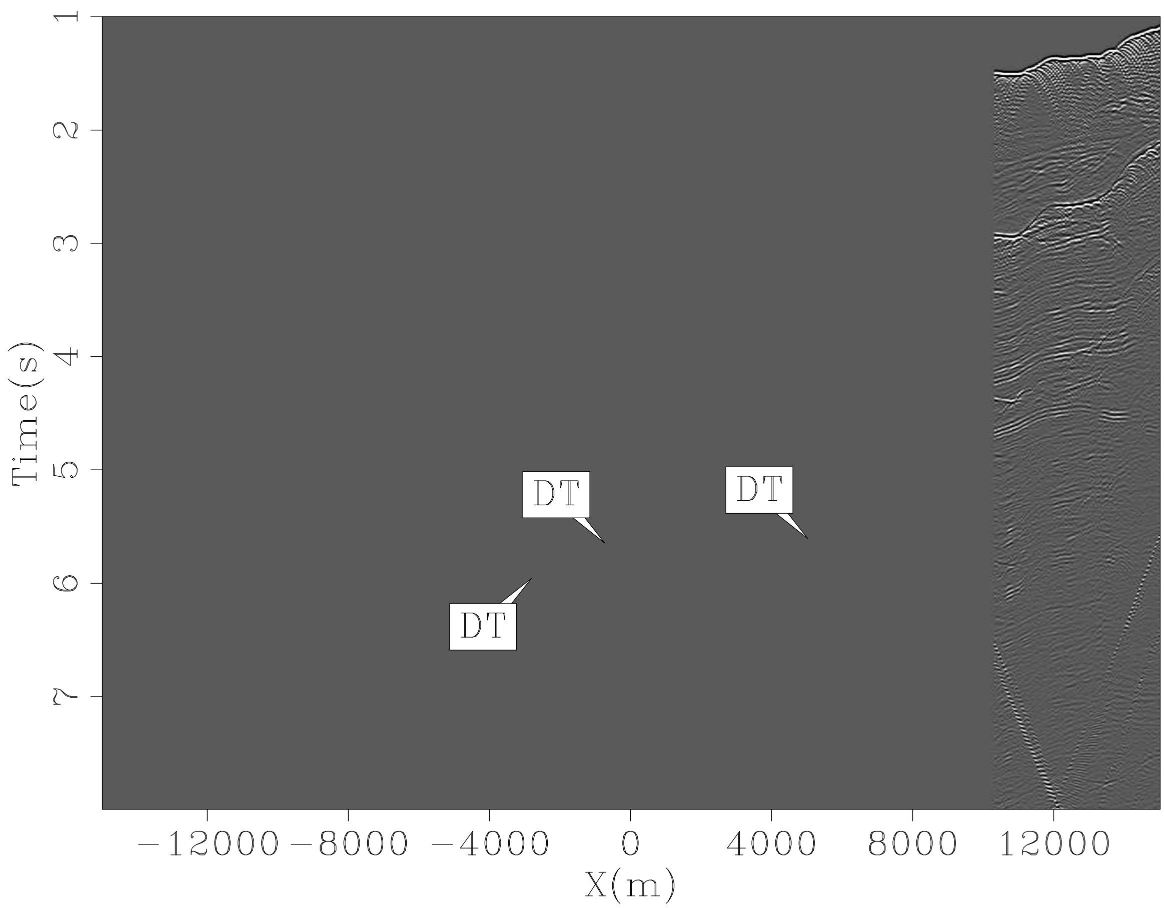

Figure 1: Constant offset section (h=500 m) of the data with multiples. DTs point to the tails of diffracted multiples. antoine2-data [ER]

Modeling of the multiples

In the shot domain, for one frequency, the multiple model is given by the spatial non-stationary convolution of shot gathers (Verschuur et al., 1992; Dragoset and Jericevic, 1998). The synthetic model has an offset spacing of 12.5 m and a shot separation of 50 m. To make the multiple prediction work, the offset axis is sampled down to 50 m. Figure 1 shows one constant offset section from -15,000 m to +15,000 m.

This section of the dataset is particularly interesting because of the diffractions visible throughout. Because no velocity model or sedimentary section is available, a possible interpretation of these diffractions is the presence of salt bodies with a rugose top (similar to what we see with the Sigsbee2B dataset). The multiple model is shown in Figure 2 for the same offset. DT points to diffraction tails where the model is not properly rendering the multiples in the data. Besides these few imperfections in the model, the model looks very faithful to the actual multiples. The pattern recognition technique and the adaptive subtraction are compared in the following section.

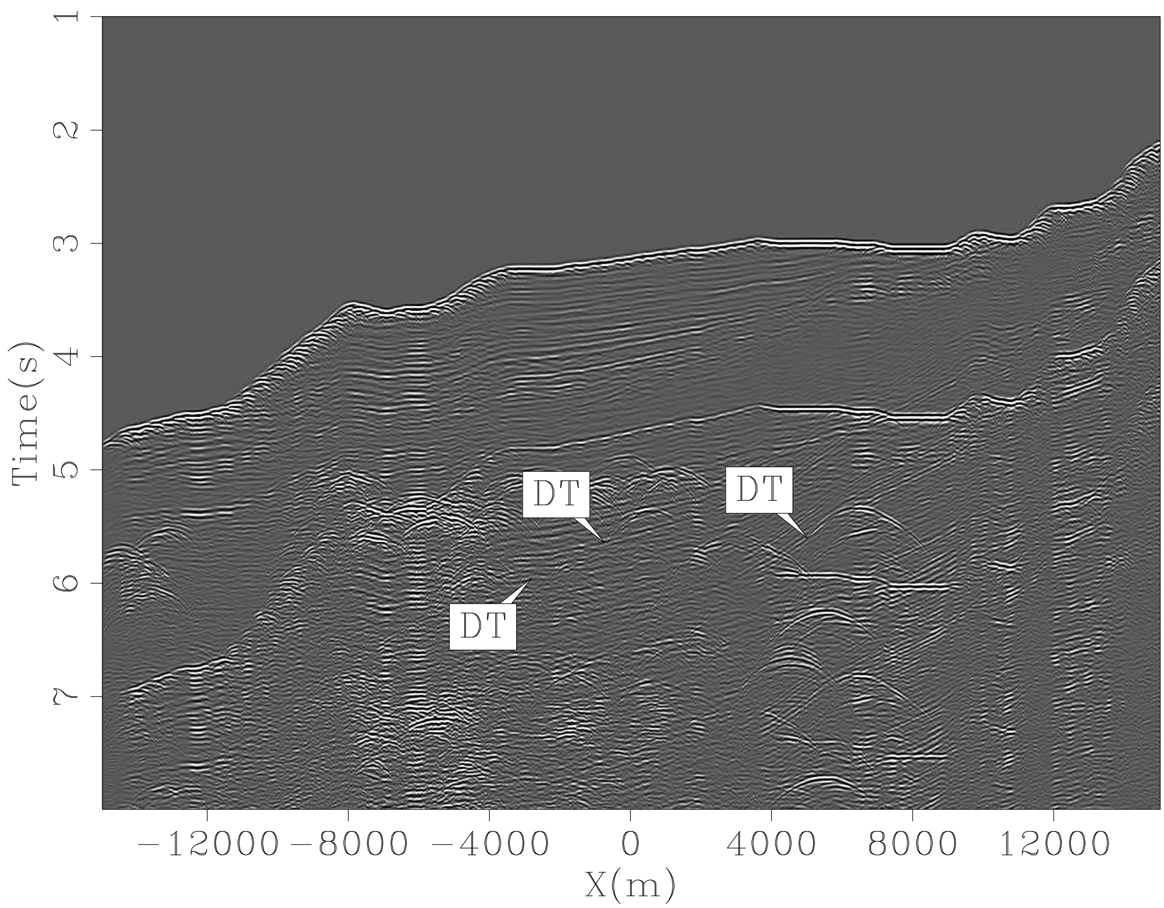

Figure 2: Constant offset section (h=550 m) of the estimated multiples. The multiples are accurately modeled except for the diffracted multiples, shown as DT, for which the limited range of offsets and number of shots hamper any attempt at modeling the diffraction tails. antoine2-mult [CR]

SIGNAL/NOISE SEPARATION RESULTS

The goal of this section is to compare the two subtraction techniques on the synthetic dataset. This dataset was primarily designed to conduct blind tests for velocity estimation methods. Consequently, no structural information is known.

The result of adaptive subtraction is shown for one offset section in Figure 3 and the result of pattern-based subtraction is shown in Figure 4. The adaptive subtraction is doing a decent job everywhere. However, some multiples are still visible. For example, '1' in Figure 3 points to a location where multiples overlap with primaries and are not attenuated. In contrast, the pattern-based subtraction technique (i.e., Figure 4) seems to do a better job attenuating these events. The same is true for arrows '2' and '5'. The diffracted multiples (arrows '3' and '4') are also better attenuated with the pattern-based technique.

Because no velocity analysis was conducted with this dataset, no stacks are presented.

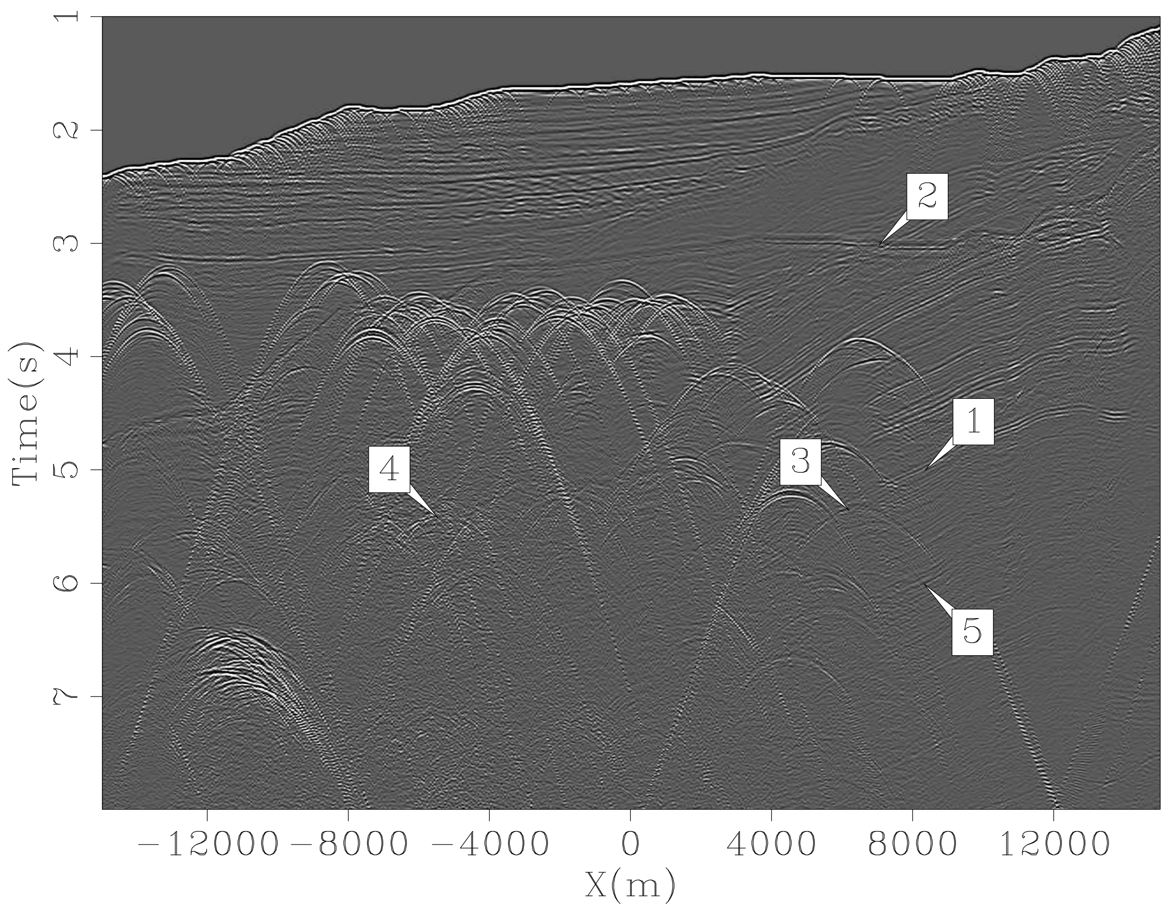

Figure 3: Constant offset section (h=550 m) of the estimated primaries with adaptive subtraction. The arrows point to locations where multiples are still present. antoine2-dsign [CR]

Alternatively, close-ups of constant offset sections are shown to illustrate strengths and weaknesses of the two different approaches. Figure 5 shows a comparison between the input data, the multiple model, the estimated primaries with the adaptive subtraction and the estimated primaries with the pattern recognition technique. The offset is 700 m. As shown by the arrows, the pattern-based method performs generally better. The same conclusions hold in Figure 6. Note in Figure 6b aliasing artifacts due to the coarse sampling of the offset axis for the multiple prediction (van Dedem, 2002).

Sometimes, it can be rather difficult to see if multiples are removed or not by simply looking at 2D planes. Figure 7c shows one event at '2' that seems to be a primary. However, by looking at the shot gathers (not shown here), it appears that this event is a multiple that the pattern-based approach was able to attenuate.

One shortcoming of the pattern-recognition technique is that it relies on the Spitz approximation to provide a signal model if nothing else is available. By construction, the signal and noise filters will span different components of the dataspace. Therefore, the estimated primaries and multiples are uncorrelated. This simple fact proves that with the Spitz approx-

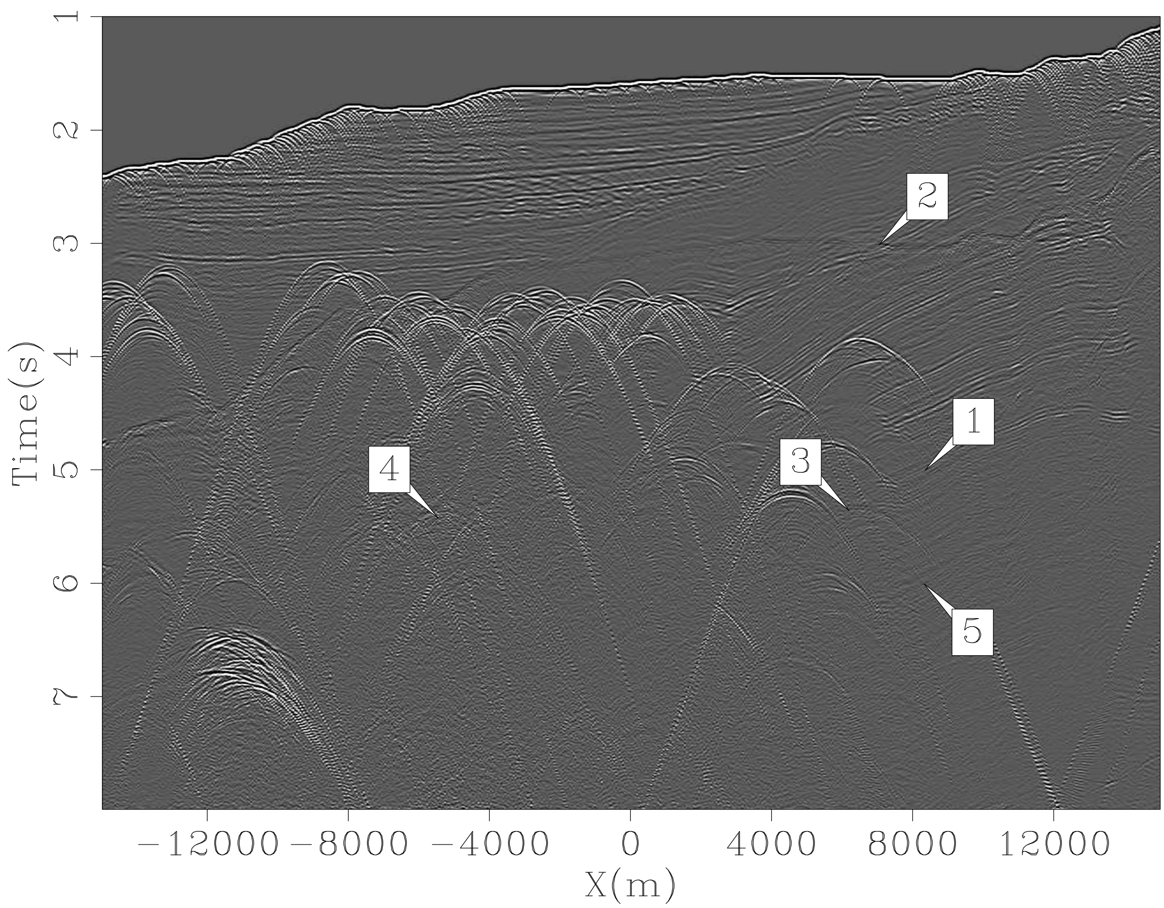

Figure 4: constant offset section (h=550 m) of the estimated primaries with pattern recognition. Multiples are better attenuated than in Figure 3. antoine2-sign [CR]

imation, higher dimension filters are preferred because primaries and multiples have fewer chances to look similar.

Figure 8 shows an example where primaries are damaged by the pattern-based method. For instance in Figure 8a, we see at '2' a primary that is attenuated by the PEFs (Figure 8d) but well preserved by the adaptive subtraction (Figure 8c). Here the primaries and multiples (Figure 8b) exhibit similar patterns. Using the Spitz approximation, event '2' is identified as noise and removed as such. For event '3', it is quite difficult to say if multiples are better removed in Figure 8d or if primaries are better preserved in Figure 8c. Looking at the corresponding shot gathers did not help to make a decision because the multiples are very strong. Event '4' looks clearly better with the adaptive subtraction and '1' and '5' are well recovered with the pattern-based approach.

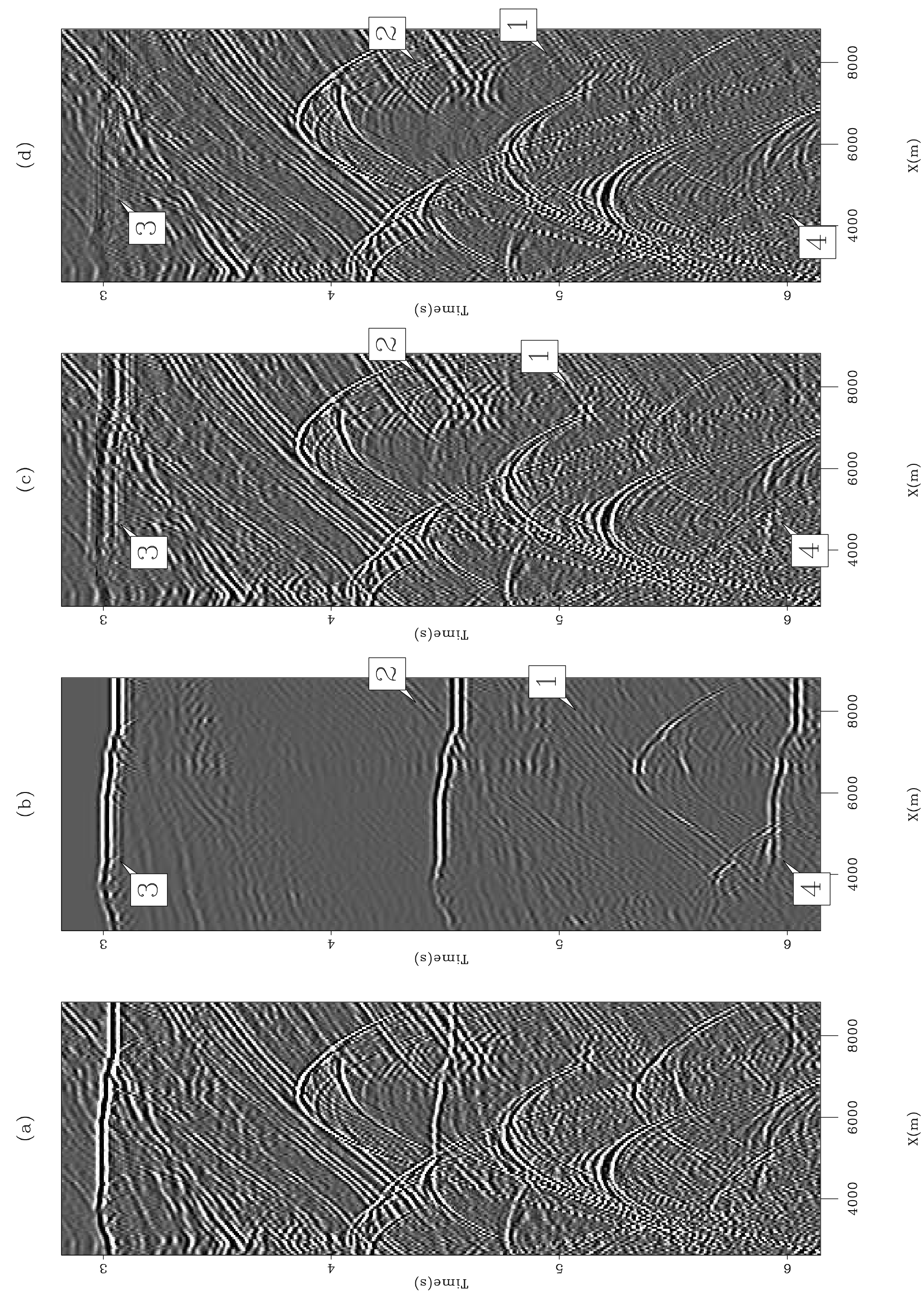

Figure 5: Constant offset sections (h=700 m) for (a) the input data, (b) the multiple model, (c) the estimated primaries with adaptive subtraction and (d), estimated primaries with the pattern-based approach. Arrows point to locations where the pattern-based approach attenuates multiples significantly better than the adaptive subtraction. antoine2-compwin1 [CR,M]

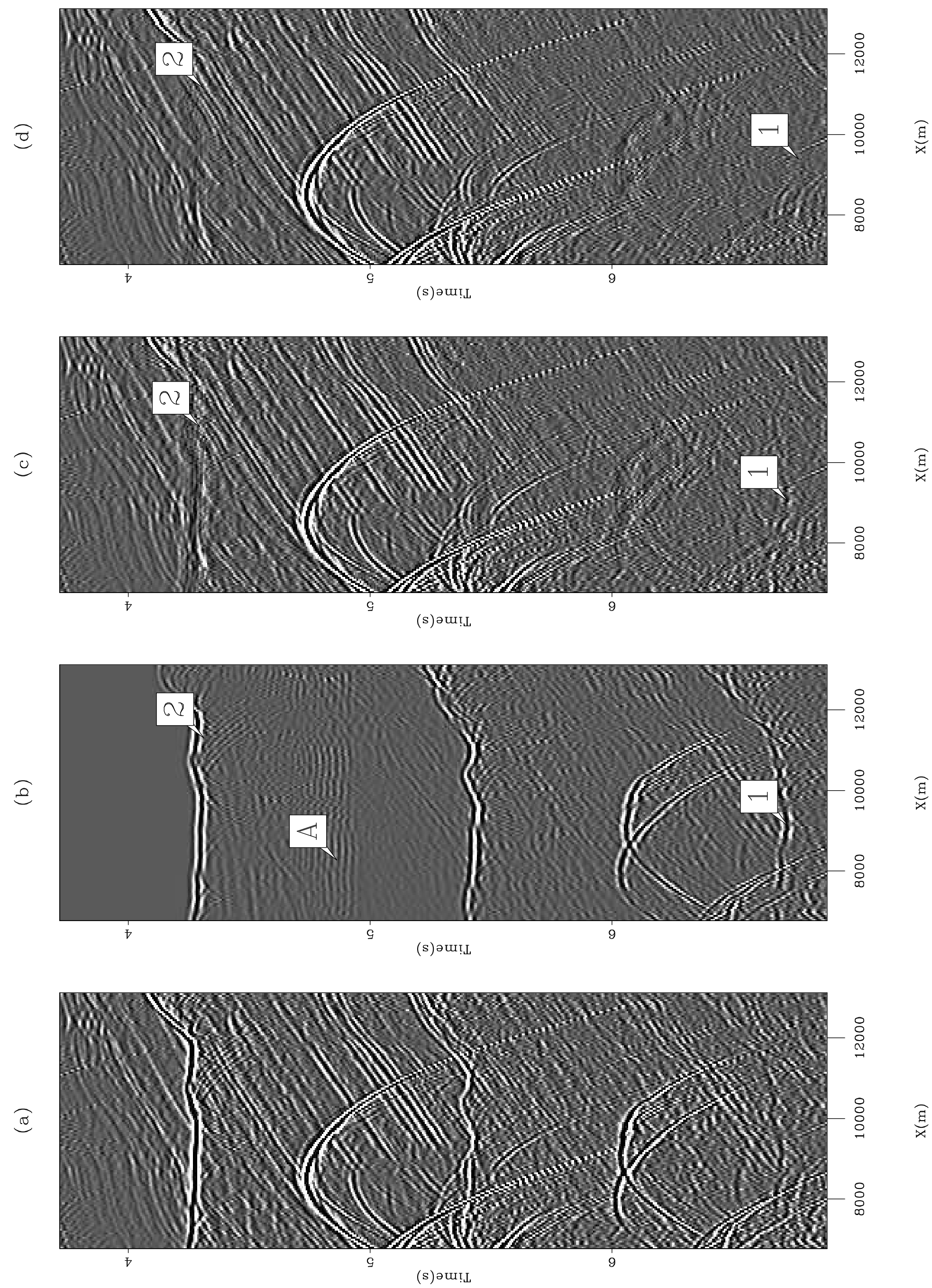

Figure 6: Constant offset sections (h=4550 m) for (a) the input data, (b) the multiple model, (c) the estimated primaries with adaptive subtraction and (d), estimated primaries with the pattern-based approach. Arrow A points to aliasing effects due to the offset sampling of the shot gathers. The pattern-based approach attenuates the multiples better than the adaptive subtraction in '1' and '2'. antoine2-compwin6 [CR,M]

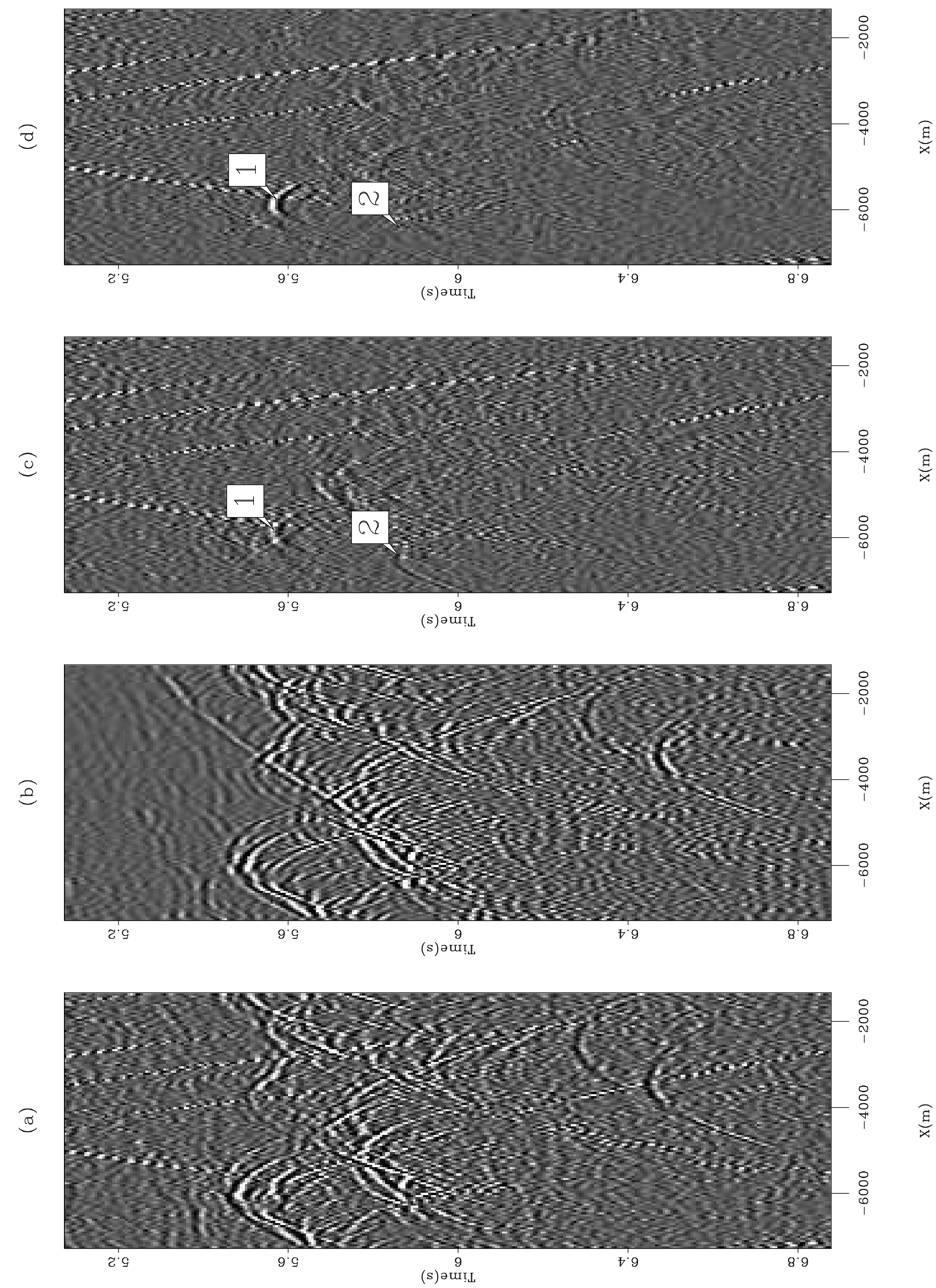

Figure 7: Constant offset sections (h=3300 m) for (a) the input data, (b) the multiple model, (c) the estimated primaries with adaptive subtraction and (d), estimated primaries with the pattern-based approach. ’1’ points to a primary that the pattern-recognition preserves very well. ’2’ points to an event that is attenuated with the pattern-based approach but not with the adaptive subtraction in (c). Though not shown here, a close inspection of the corresponding shot gathers suggests that ’2’ is actually a multiple. antoine2-compwin8 [CR,M]

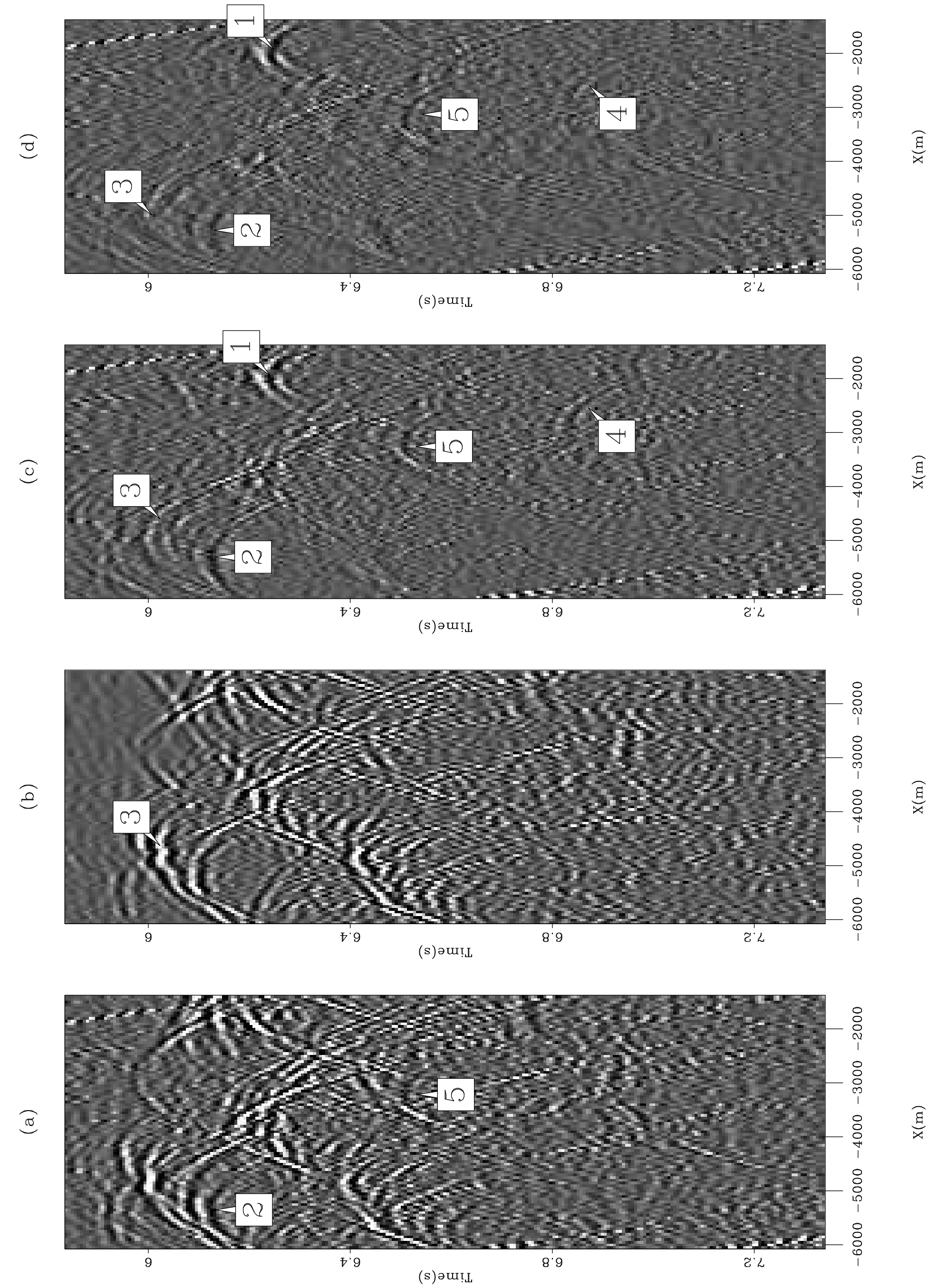

Figure 8: Constant offset sections (h=5050 m) for (a) the input data, (b) the multiple model, (c) the estimated primaries with adaptive subtraction and (d), estimated primaries with the pattern-based approach. '1' and '5' show events better preserved with the pattern-based method. '2' and '1' are better recovered with the adaptive subtraction. '4' seems to point to a primary that the adaptive subtraction is able to save. '3' is undecided. antoine2-compwin12 [CR,M]

CONCLUSION

Two methods for subtracting surface-related multiples were presented. One method removes the multiples by adaptive subtraction, assuming that the primaries have minimum energy. One method removes the multiples with a pattern-recognition technique, assuming that the primaries and multiples have different multivariate spectra (patterns). Tests on a 2D synthetic dataset show that the pattern-based technique tends to separate primaries and multiples better than adaptive subtraction. In cases where the primaries and multiples are correlated, however, pattern-recognition can damage primaries. This effect is amplified by the Spitz approximation which prevents the noise and signal PEFs from spanning similar areas of the data space.

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