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Multidimensional multiple attenuation in complex geology: illustration on the Sigsbee2B dataset

Antoine Guitton[1]

ABSTRACT

A pattern-based multiple attenuation technique is tested on the Sigsbee2B dataset. The results of multiple removal are analyzed in the image space after migration to better understand the impact of this process on the primaries. When an accurate model of the primaries (signal) and the multiples (noise) exist for the estimation of the noise and signal annihilation filters (i.e., non-stationary multidimensional prediction-error filters), this method removes the multiples extremely well while preserving the primaries. When the model of the multiples is provided by the Spitz approximation, which consists in convolving the data with the noise annihilation filters to get a signal model, good results are obtained if 3D filters are utilized.

INTRODUCTION

In the presence of complex geology where multipathing, illumination gaps, and coherent noise are present, the most advanced techniques need to be used for both preprocessing and imaging. For multiple attenuation, it has been established that methods that take the wavefield propagation into account (e.g., Verschhur et al. (1992); Weglein et al. (1997)) are the most successful in complex geology (Matson et al., 1999; Bishop et al., 2001; Paffenholz et al., 2002).

For multiple removal in complicated geology, the standard processing workflow is usually divided into a prediction step (i.e., modeling of the multiples) and a subtraction step. In the subtraction step, multiples are removed according to some assumptions made on the signal distribution (primaries) in the data. Assuming that the signal has minimum energy, the multiple model is often simply subtracted by adaptive subtraction with a ℓ^2 norm. However, the least-squares assumption might not hold all the time (Spitz, 1999). For instance, Guitton and Verschuur (2004) show that when primaries are much stronger than the multiples, the ℓ^1 norm should be used instead. In Guitton (2003b), I showed that a subtraction scheme based on the assumption that both primaries and multiples have different patterns leads to a successful separation. This technique approximates the multivariate spectrum (patterns) of the noise and signal with non-stationary multidimensional prediction-error filters (PEFs).

In this paper, I investigate the multiple attenuation technique with multidimensional PEFs with the Sigsbee2B dataset. This dataset is particularly challenging due to the complex geom-

[1]**email:** antoine@sep.stanford.edu

etry of the salt body. In the ideal case where an accurate noise (multiples) and signal model are known in advance, the PEF processing leads to an excellent attenuation of the multiples. If only a multiple model is known such as with the Delft approach, 3D filters should be used instead of 2D filters. This result is consistent with the conclusions in Guitton (2003b).

Often in the processing of multiples, the final results are displayed on common shot gathers, common offset sections or stacks. Because the end-product of the seismic processing workflow is always a migrated image, the outcome of a multiple attenuation technique should be analyzed in the image space (after migration) as often as possible. Therefore, I will concentrate most of my efforts in displaying multiple attenuation results in the image space with migrated images at zero-offset and angle domain common-image gathers (ADCIG).

In the next section, I derive the basic equations governing the multiple attenuation technique with multidimensional PEFs. Then, I present the results of multiple attenuation on the Sigsbee2B dataset with or without a known signal model and when 2D or 3D filters are used.

THEORY OF MULTIPLE ATTENUATION AND FILTER ESTIMATION

The key assumption of the proposed multiple attenuation technique is that the primaries and multiples have different multidimensional spectra that PEFs can approximate (Claerbout, 1992; Spitz, 1999). In this approach, the multiple attenuation is similar to Wiener filtering (Abma, 1995). One important approximation is that the multiples and primaries are uncorrelated so that the cross-spectrum between them is not needed. Multiple attenuation with multidimensional PEFs is performed in two steps. First the PEFs for the multiples and primaries are estimated. Then multiples are separated from the primaries. In the next section, I describe the multiple removal step first, assuming that the PEFs for both the primaries and multiples are known. Then I describe how PEFs are estimated and show how the signal PEFs can be computed when no signal model is given, leading to the Spitz approximation.

Multiple attenuation

First consider that any seismic data $\mathbf{d}$ are the sum of signal (primaries) and noise (multiples) as follows:

$$\mathbf{d} \;=\; \mathbf{s}+\mathbf{n}, \tag{1}$$

where $\mathbf{s}$ is the signal we want to preserve and $\mathbf{n}$ the noise we wish to attenuate.

Now assuming that the multidimensional PEFs $\mathbf{N}$ and $\mathbf{S}$ are known for the noise and signal components, respectively (see the following section for a complete description of the PEFs estimation step), we have

$$\begin{aligned} \mathbf{Nn} &\approx \mathbf{0}, \\ \mathbf{Ss} &\approx \mathbf{0}, \end{aligned} \tag{2}$$

by definition of the PEFs. Equations (1) and (2) can be combined to solve a constrained problem to separate signal from noise as follows:

$$\begin{array}{rcccl} \mathbf{0} & \approx & \mathbf{r_n} & = & \mathbf{Nn}, \\ \mathbf{0} & \approx & \mathbf{r_s} & = & \mathbf{Ss}, \\ \text{subject to} & \leftrightarrow & \mathbf{d} & = & \mathbf{s}+\mathbf{n}. \end{array} \tag{3}$$

The noise $\mathbf{n}$ can be eliminated in the last equation of the fitting goal (3) by convolving with $\mathbf{N}$. Doing so, equation (3) becomes:

$$\begin{array}{rcccl} \mathbf{0} & \approx & \mathbf{r_n} & = & \mathbf{Ns}-\mathbf{Nd}, \\ \mathbf{0} & \approx & \mathbf{r_s} & = & \mathbf{Ss}. \end{array} \tag{4}$$

Sometimes it is useful to add a masking operator on the noise and signal residuals $\mathbf{r_n}$ and $\mathbf{r_s}$ when performing the noise attenuation. It happens for example when we want to isolate and preserve parts of the data where no multiples are present. For instance, a mute zone can be taken into account very easily. Calling $\mathbf{M}$ this masking operator, the fitting goals in equation (4) are weighted as follows:

$$\begin{array}{rcccl} \mathbf{0} & \approx & \mathbf{r_n} & = & \mathbf{M}(\mathbf{Ns}-\mathbf{Nd}), \\ \mathbf{0} & \approx & \mathbf{r_s} & = & \mathbf{MSs}. \end{array} \tag{5}$$

Solving for $\mathbf{s}$ in a least-squares sense leads to the objective function

$$f(\mathbf{s}) = \|\mathbf{r_n}\|^2 + \epsilon^2\|\mathbf{r_s}\|^2, \tag{6}$$

where ϵ is a trade-off parameter that relates to the signal/noise ratio. The least-squares inverse for $\mathbf{s}$ becomes

$$\hat{\mathbf{s}} = (\mathbf{N}'\mathbf{MN}+\epsilon^2\mathbf{S}'\mathbf{MS})^{-1}\mathbf{N}'\mathbf{MNd}, \tag{7}$$

where ($'$) stands for the adjoint. Soubaras (1994) uses a very similar approach for random noise attenuation and more recently for coherent noise attenuation (Soubaras, 2001) with F-X PEFs. Because the size of the data space can be quite large, $\mathbf{s}$ is estimated iteratively with a conjugate-gradient method. In the next section, I describe how both $\mathbf{N}$ and $\mathbf{S}$ are estimated.

Filter estimation

The PEFs are time-space domain non-stationary filters to cope with the variability of seismic data with time, offset and shot position. The basic equations for non-stationary PEFs estimation are (Guitton, 2003b):

$$\begin{array}{rcccl} \mathbf{0} & \approx & \mathbf{r_y} & = & \mathbf{YKa}+\mathbf{y}, \\ \mathbf{0} & \approx & \mathbf{r_a} & = & \mathbf{Ra}, \end{array} \tag{8}$$

where $\mathbf{Y}$ is a non-stationary combination matrix (Margrave, 1998), $\mathbf{K}$ is a masking operator, $\mathbf{a}$ a vector of the unknown PEFs coefficients, $\mathbf{y}$ the data vector from which we want to estimate the PEFs and $\mathbf{R}$ a regularization operator.

Often with seismic data, the amplitude varies across offset, midpoint and time. These amplitude variations can be troublesome with least-squares inversion because they tend to bias the final result (Claerbout, 1992). Therefore, it is important to make sure that these amplitude variations do not affect our processing. One solution is to apply a weight to the data like Automatic Gain Control (AGC) or a geometrical spreading correction. However, a better way is to incorporate this weight inside the inversion by scaling the residual (Guitton, 2003a). Introducing a weighting function **W** in the PEFs estimation leads to:

$$\begin{array}{rcccl} \mathbf{0} & \approx & \mathbf{r_y} & = & \mathbf{W}(\mathbf{YKa}+\mathbf{y}), \\ \mathbf{0} & \approx & \mathbf{r_a} & = & \mathbf{Ra}. \end{array} \quad (9)$$

As shown by Guitton (2003a), this weighting improves the signal/noise separation results and can incorporate a mute zone where no PEFs are to be estimated. This weight can be different for the noise and the signal PEFs. Estimating **a** in a least-squares sense gives:

$$f(\mathbf{a}) = \|\mathbf{r_y}\|^2 + \epsilon^2 \|\mathbf{r_a}\|^2, \quad (10)$$

which leads to the least-squares estimate of **a**

$$\hat{\mathbf{a}} = -(\mathbf{K'Y'W}^2\mathbf{YK} + \epsilon^2\mathbf{R'R})^{-1}\mathbf{K'Y'W}^2\mathbf{y}. \quad (11)$$

Because many filter coefficients are estimated, **a** is estimated iteratively with a conjugate-gradient method.

Now, prior to the signal estimation in equation (5), **S** and **N** need to be computed from a signal and noise model, respectively. The multiple model is often (but not necessarily) derived by auto-convolving the recorded data (Verschhur et al., 1992), thus obtaining a prestack model of the multiples later used to estimate a bank of non-stationary PEFs **N**.

At this stage, a key assumption is that the relative amplitude of all order of multiples is preserved. In theory, an accurate surface-related multiple model can be derived if (1) the source wavelet is known, (2) the surface coverage is large enough, and (3) all the terms of the Taylor series that model different orders of multiples are incorporated (Verschhur et al., 1992). In practice, however, a single convolution is performed (first term of the Taylor series) which gives a multiple model with erroneous relative amplitude for high-order multiples (Wang and Levin, 1994; Guitton et al., 2001). In addition, the surface coverage might not be sufficient. This can generate wrong amplitudes for short offset traces and complex structures. Because PEFs estimate patterns, wrong relative amplitude can affect the noise estimation. However, as we shall see later, 3D filters seem to better cope with noise modeling inadequacies.

The signal PEFs are more difficult to estimate since the signal is usually unknown. However, Spitz (1999) shows that for uncorrelated signal and noise, the data PEFs **D** can be approximated with

$$\mathbf{D} = \mathbf{SN}. \quad (12)$$

As demonstrated by Claerbout and Fomel (2000), equation (12) is a good approximation for the data PEFs because PEFs are important where they are small. Both **N** and **D** can be estimated from the model of the multiples and the data (primaries plus multiples), respectively.

Estimation of the signal PEFs involves a deconvolution in equation (12) that can be unstable with non-stationary filters. To avoid the deconvolution step, the noise PEFs are convolved with the data:

$$\mathbf{u} = \mathbf{N}\mathbf{d}. \tag{13}$$

Then the PEFs $\mathbf{U}$ are estimated for $\mathbf{u}$ such that

$$\mathbf{U}\mathbf{u} = \mathbf{U}\mathbf{N}\mathbf{d} \approx \mathbf{0}. \tag{14}$$

From Spitz's approximation in equation (12), the following relationships hold:

$$\mathbf{U}\mathbf{N} = \mathbf{D} = \mathbf{S}\mathbf{N}, \tag{15}$$

and $\mathbf{U} = \mathbf{S}$. Therefore, by convolving the data with the noise PEFs, signal PEFs consistent with the Spitz approximation can be computed. Equation (12) insures that the PEFs $\mathbf{S}$ and $\mathbf{N}$ will not span similar components of the data space.

Thanks to the Helix (Mersereau and Dudgeon, 1974; Claerbout, 1998), the PEFs can have any dimension. In this paper, I use 2D and 3D filters and demonstrate that 3D filters lead to the best noise attenuation result. When 2D filters are used, the multiple attenuation is performed on one shot gather at a time. When 3D filters are used, the multiple attenuation is performed on one macro-gather at a time. A macro-gather is a cube made of fifty consecutive shots with all the offsets and time samples. When the multiple attenuation is done, the macro-gathers are reassembled to form the final result. There is an overlap of five shots between successive macro-gathers. In the next section, I show a prestack multiple attenuation example with the synthetic Sigsbee2B dataset.

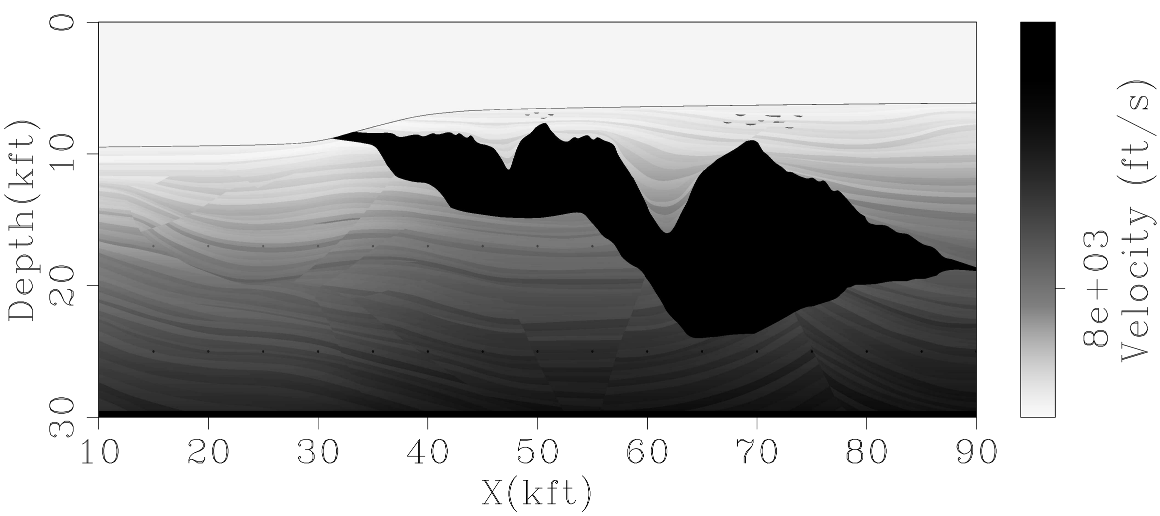

Figure 1: Stratigraphic interval velocity model of the Sigsbee2B dataset. antoine1-stratigraphy [ER]

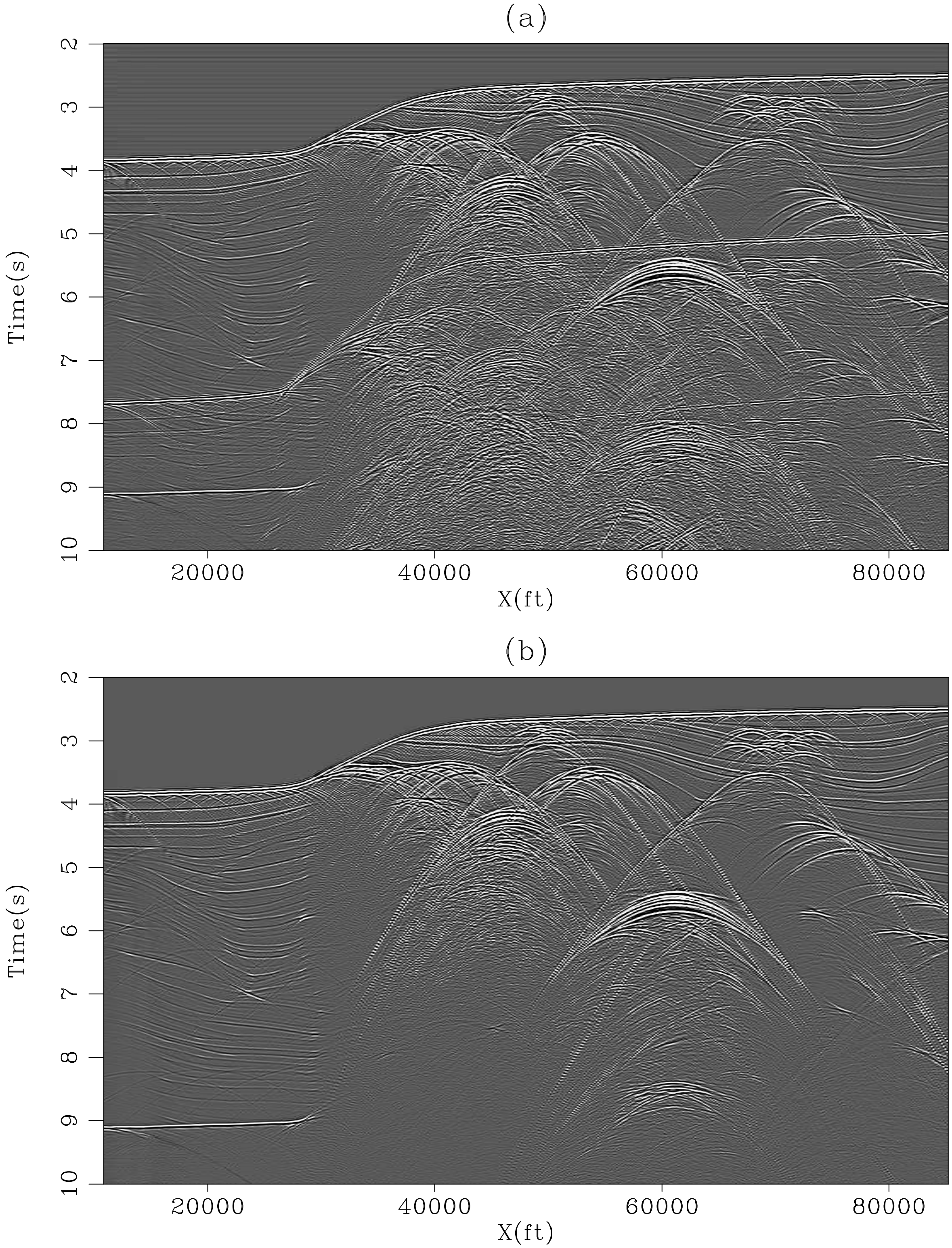

Figure 2: Two constant offset sections (h=1125 ft) of the Sigsbee2B dataset with (a) and without (b) free surface condition. The multiples are very strong below 5 s. antoine1-datasignal [ER,M]

ATTENUATION OF MULTIPLES WITH THE SIGSBEE2B DATASET

The Sigsbee2B dataset was designed to generate strong surface-related multiples. Figure 1 shows the true stratigraphic interval velocity model for this dataset. The data were created with a 2D acoustic finite difference modeler with constant density. Two datasets were generated: one with a free surface (Figure 2a) and one without a free surface (Figure 2b). These two datasets are such that a direct subtraction of the two leads to an almost true prestack model of the surface-related multiples. Because this multiple attenuation technique deals with the subtraction step only, the multiple model obtained by subtraction of the two datasets with and without free-surface conditions is used for the noise PEFs estimation for all my computations.

As stated in the introduction, I focus my analysis in the image space after migration. In complex geology, multiple attenuation results should always be assessed after migration; the effects of the multiple attenuation technique on the amplitudes of the primaries in ADCIGs (e.g., Figure 3), or on migrated images at zero offset (e.g., Figure 4) can be then directly assessed. For the Sigsbee2B dataset, a split-step double square-root (DSR) migration code with three reference velocities is used.

Ideally, because the data were created with finite differences, a finite differences migration code should be used to take the full complexity of the wave propagation into account. Figure 3d illustrates the limits of the migration algorithm by showing non-flat events below the salt. In contrast, Figure 3b displays flat gathers in the sedimentary section left of the salt body. An illumination effect is clearly visible below 20,000 ft, between 20 and 30 deg in Figure 3b. Figures 3a and 3c highlight the effects of the multiples on ADCIG by creating numerous artifacts and fictitious events.

It is interesting and somewhat surprising to see that in Figure 4a the multiples are very weak after migration below the salt compared to the constant offset sections in Figure 2a. In particular, the water bottom multiple seems to disappear. This is because the multiples are extremely distorted by the migration process in the vicinity of the complex salt structure. Compared with the migration of the primaries only in Figure 4b, the multiples in Figure 4a are masking a lot of primaries in the deepest part of the model and thus need to be removed.

In the next section, I demonstrate that in the ideal case where a model for both the primaries and multiples exist, the primaries can be recovered with almost no bias from the attenuation technique. Then, without any model for the primaries, I show that the Spitz approximation gives an excellent multiple attenuation result when 3D filters are used.

Estimating biases

A bias is a processing footprint left by the multiple attenuation technique, e.g., edge effects from the non-stationary PEFs. In an ideal but unrealistic case, a model for both the primaries and the multiples might be available. In this case, a bias is also any difference between the true primaries and the estimated primaries after attenuation of the multiples. In this section I demonstrate that the bias is minimum with the pattern-based approach.

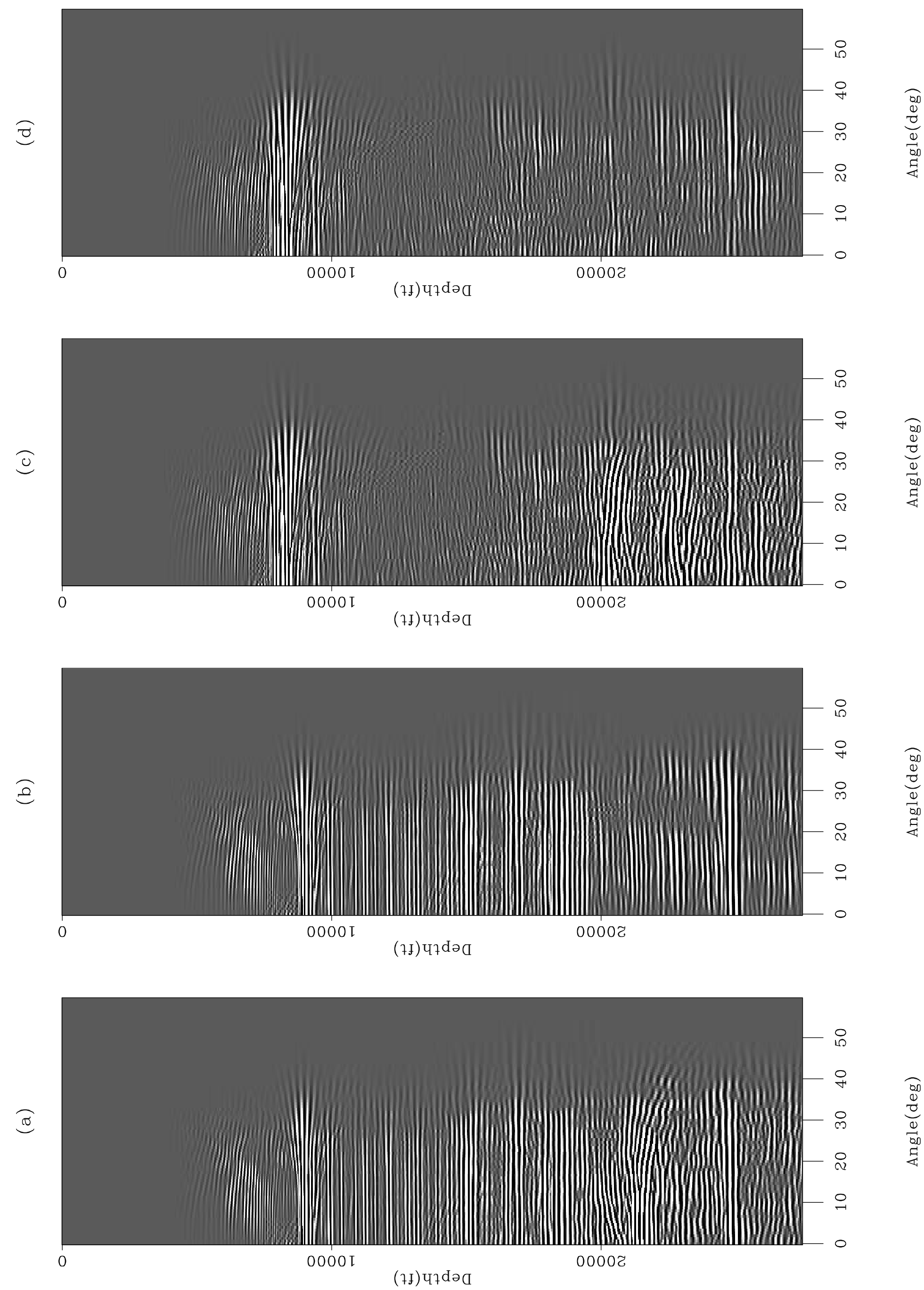

Figure 3: ADCIGs for the migrated data at two different surface locations inside (i.e., 33 kft) and outside (i.e., 30 kft) the salt boundaries. (a) ADCIG at 30 kft for the data with multiples. (b) ADCIG at 30 kft for the data without multiples. (c) ADCIG at 33 kft for the data with multiples. (d) ADCIG at 33 kft for the data without multiples. Theoretically, with the appropriate migration algorithm, this last gather should be flat everywhere. antoine1-datasignal2-ang [CR,M]

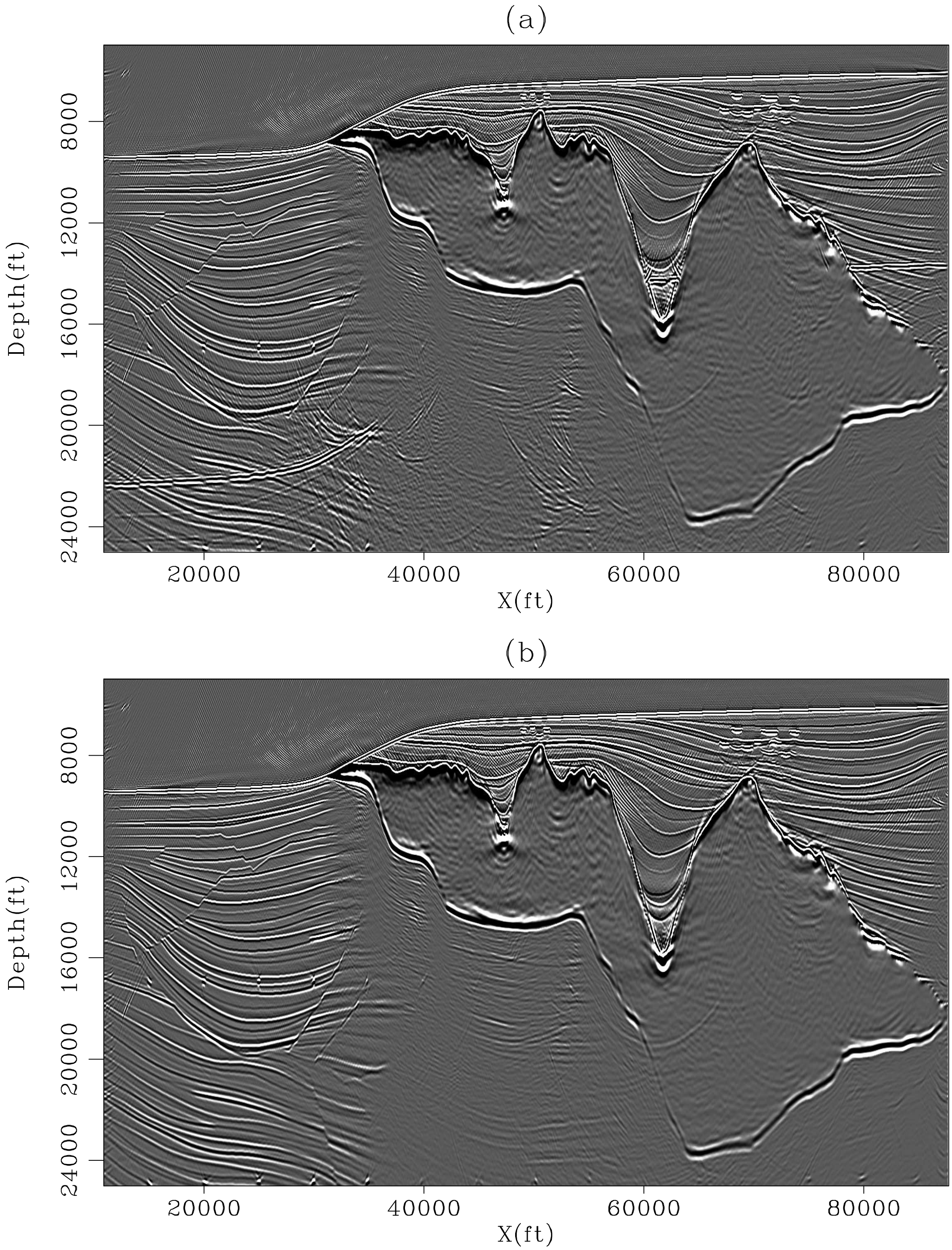

Figure 4: Migrated images at zero-offset for the data with (a) and without (b) free surface condition. Comparing with Figure 2, the multiples appear much weaker below the salt after migration. However, some reflectors near 22 kft are hidden in (a). antoine1-datasignal-mig [CR,M]

For the model of the primaries, the answer, i.e., the data modeled without the free surface condition is used. For the multiples, the difference between the modeled data with (Figure 2a) and without (Figure 2b) free surface is used. Because the noise and signal PEFs are estimated from almost the exact answer, only 2D filters are estimated. 3D filters can help if the primaries and multiples are correlated in time and offset but uncorrelated across shot position. With 2D filters, the attenuation is performed one shot gather at a time. Figure 5a displays the estimated primaries and Figure 5b the difference with the true primaries (Figure 2b). The bias introduced by the attenuation method is very small. 3D filters would have probably given better results where the difference between Figure 5a and 2b is the strongest (e.g., near 60 kft).

Looking now at the same estimated primaries after migration in Figure 6a, we see again that the attenuation gives an excellent result with almost no bias. Some energy is visible in the difference plot in Figure 6b between Figures 6a and 4b where no multiples are actually present. These artifacts come from the fact that the modeled data with and without free surface condition are not perfectly similar where the primaries are located.

From these results it appears that the quality of the multiple attenuation depends essentially on the filters. If the primaries and multiples are known, the primaries with almost no bias are recoverable. Therefore, we should always try to find the best models for the signal and the noise. In practice, a very accurate model of the multiples can be estimated with the auto-convolutional process of the Delft approach. For the primaries, the next section shows that the Spitz approximation gives a very good model if 3D filters are used.

Testing the Spitz approximation

Now I assume that only a model of the multiples is known. The Spitz approximation in equation (12) shows how the PEFs for the signal can be estimated. Because deconvolution with non-stationary filters is unstable, the noise PEFs is convolved with the data and the signal PEFs is then estimated from the convolution result.

The primaries are recovered with 2D and 3D filters. Figure 7 displays two constant offset sections after multiple attenuation with 2D and 3D PEFs. 3D PEFs give by far the best results and attenuate multiples very well. After migration, we see again in Figure 8 that the 3D PEFs better attenuate the multiples. A close-up in Figure 9 demonstrates in more detail how the two results with 2D or 3D filters differ below the salt. Events are more continuous and better preserved with 3D filters. Comparing with the true reflectors in Figure 9a, important primaries are attenuated with both 2D and 3D filters. This is particularly true where the signal is the weakest (between midpoint positions 35 and 50 kft).

This important observations could not have been made before migration in the prestack domain because the primaries are much weaker than the surface-related multiples below the salt. This illustrates the point that for complex geology, the quality of a multiple removal technique should be assessed in the image space as often as possible. For this analysis to be successful, accurate velocity and migration algorithm must be provided as well. Finally, the fact that some primaries are attenuated in Figure 9 should motivate us in devising improved strategies for building better noise and signal models.

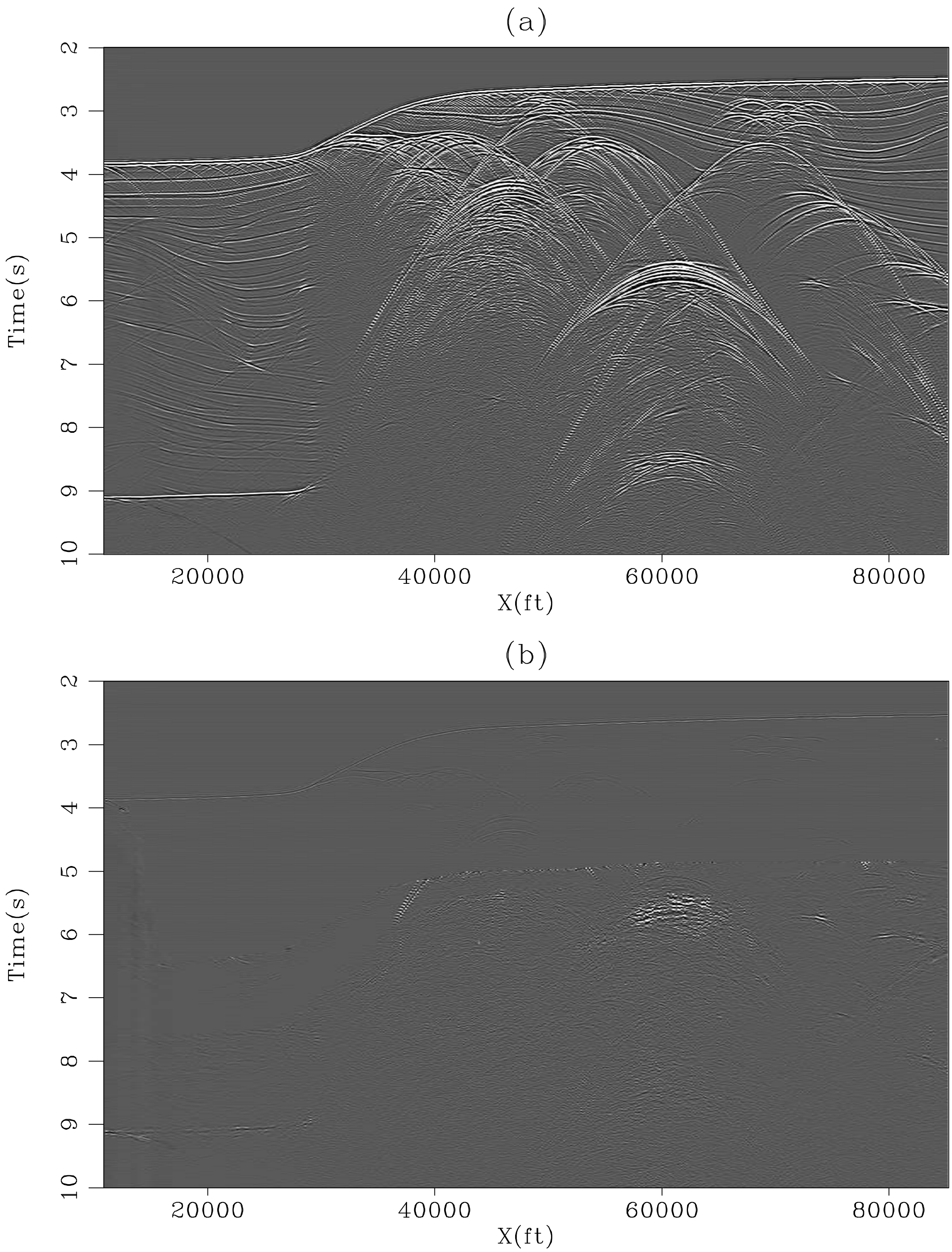

Figure 5: Two constant offset panels at h=1125 m. for the estimated primaries (a) and the difference with the true primaries (b). The true primaries and multiples are used to estimate the PEFs. antoine1-signal-true [CR,M]

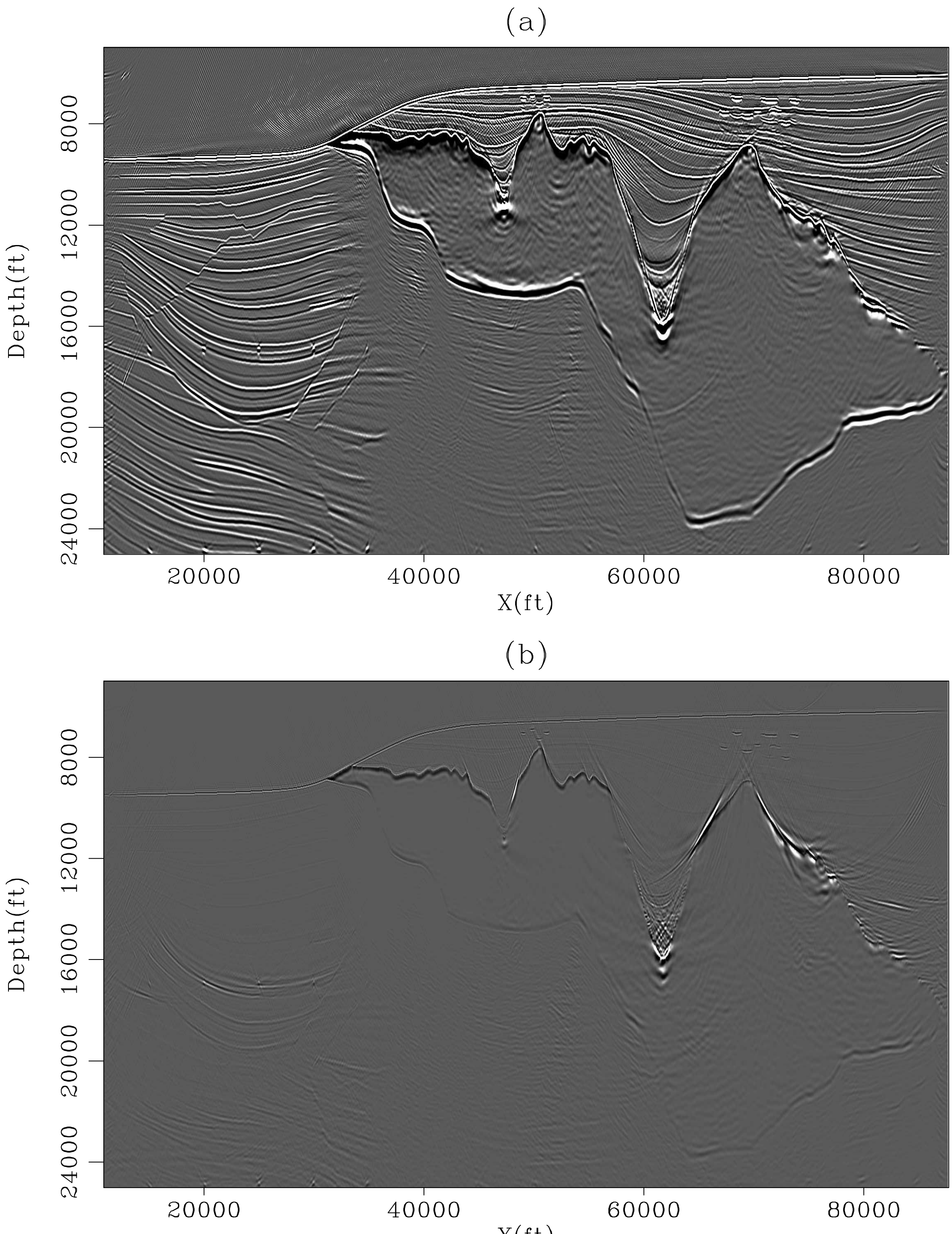

Figure 6: (a) Migration result after multiple attenuation when the true primaries and multiples are used to estimate the PEFs. (b) Difference between (a) and Figure 6b. The estimated primaries are almost exact. antoine1-signal-true-mig [CR,M]

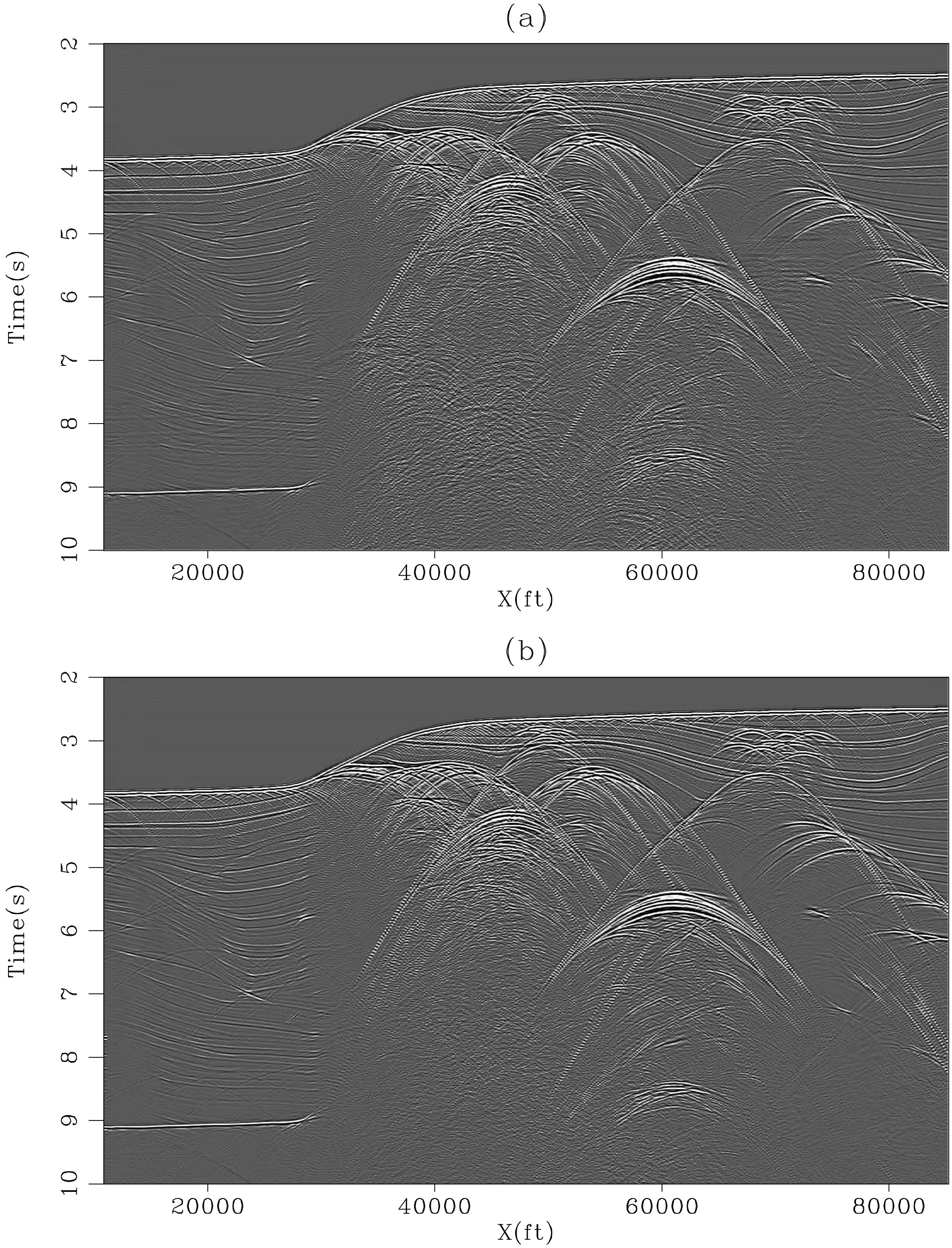

Figure 7: Two constant offset sections (h=1125 ft) after multiple attenuation with the Spitz approximation using (a) 2D and (b) 3D filters. antoine1-signal-2D-3D-PEF [CR,M]

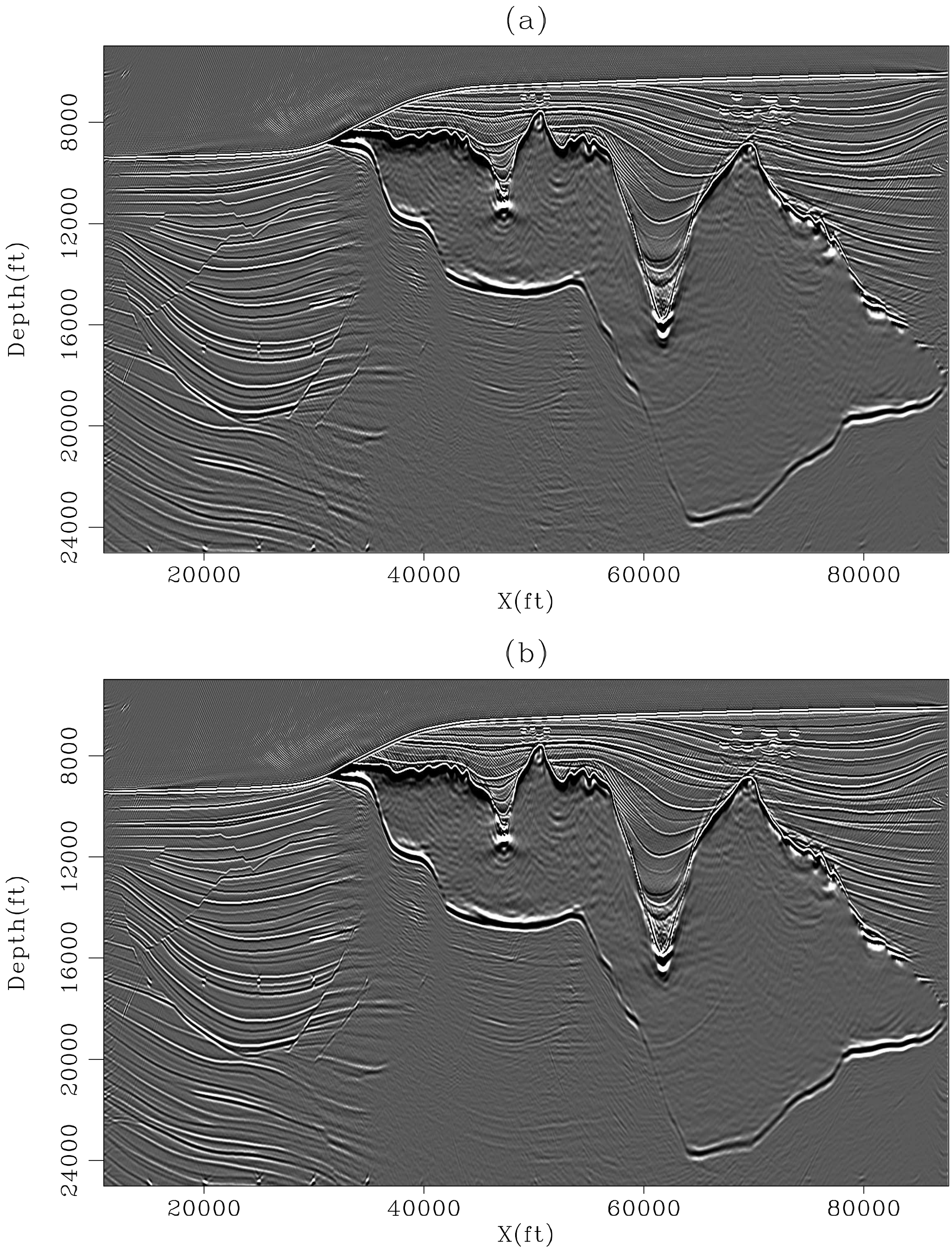

Figure 8: Two migration results of the estimated primaries with (a) 2D and (b) 3D filters. antoine1-signal-2D-3D-PEF-mig [CR,M]

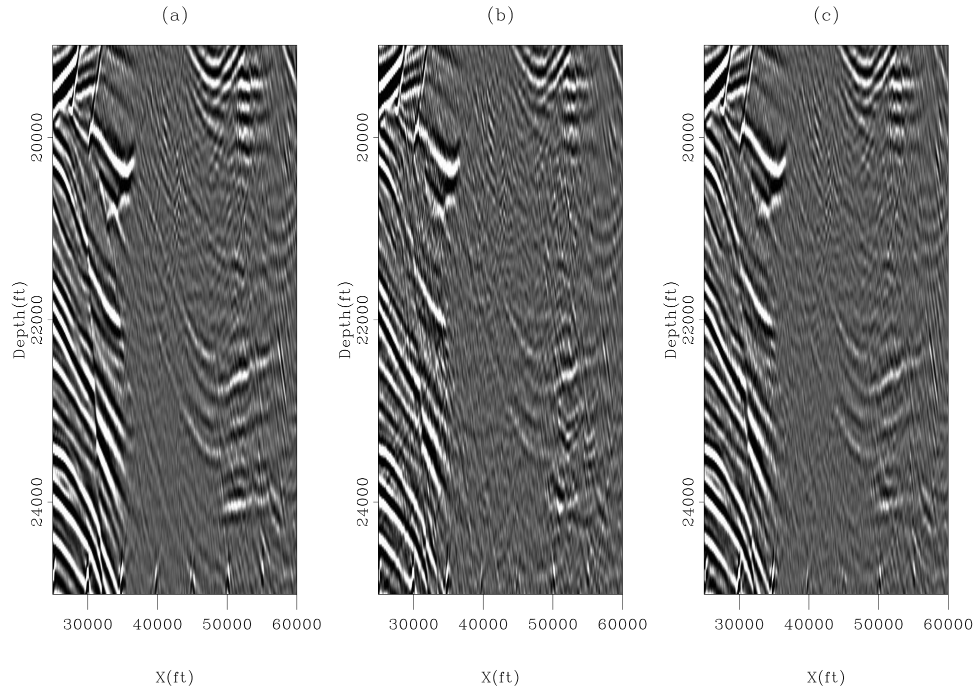

Figure 9: Close-up of Figure 8 showing two migrated images when (b) 2D and (c) 3D filters are used. The true primaries are shown in (a). antoine1-signal-2D-3D-PEF-small-mig [CR,M]

DISCUSSION-CONCLUSION

I demonstrated with the Sigsbee2B dataset that multiples can be reliably attenuated without introducing artifacts and/or damaging primaries as long as very accurate models for both noise and signal are provided. Because it is often not possible to obtain such a model for the signal, the Spitz approximation is used. As such, the Spitz approximation yields a very good separation of primaries and multiples with 3D filters. However, analyzing this separation in the image space, we notice that some weak primaries are attenuated.

This illustrates the necessity to evaluate multiple removal techniques on migrated images as much as possible. Different improvements are possible to make the noise removal better; for instance, by changing the trade-off parameter in equation (7). In addition, estimated primaries with 3D filters could be used as a signal model for a new iteration of multiple removal. Another possibility is to migrate the multiple model and apply the PEFs in the image space directly. There the effects of multiple removal could be quantified in a more interactive way.

Therefore, in addition to the fact that the image space should be used as much as possible for multiple removal, for quality control and/or attenuating multiples (Sava and Guitton, 2003), one important lesson learned with this dataset is that finding an accurate model for primaries and multiples before noise removal is crucial. We can relate this to the need for imaging to find the right velocity model; to paraphrase Claerbout (1999), everything depends on it.

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