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Multiple attenuation: data space vs. image space - A real data example

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ABSTRACT

Multiples can be attenuated either before or after the imaging process. Adaptive subtraction can be applied after migration to eliminate the multiples in the image space. We build a multiple model based on the sea floor reflection, that is kinematically correct. We then perform multiple attenuation to remove the water-bottom multiple in both the image space and the data space.

INTRODUCTION

Multiples are often the most significant impediment to the successful construction and interpretation of marine seismic and ocean bottom seismic data. There are several techniques for multiple removal. The selection of the most appropriate method depends on, among other factors, the geology, the acquisition methods and the processing costs. Examples of possible methods include: 1) multiple separation with a high-resolution hyperbolic Radon Transform (Lumley et al., 1995; Kostov and Nichols, 1995), which depends on a observable difference between the moveout of the primaries and multiples; and 2) surface-related multiple elimination (SRME) (Verschuur et al., 1992), which works better on areas with a difficult-to-distinguish difference between the moveout of the primaries and multiples.

Where to perform the multiple elimination, in the data space (before imaging) or in the image space (after imaging), is also a variable to consider when attenuating the multiples. Sava and Guitton (2003) conclude that multiples can be eliminated after migration, in the angle-domain, using Radon Transforms. Guitton (2004) suggests that the image space should be used as much as possible for the multiple-suppression process, since one of the final products of the seismic processing workflow is a migrated image. This paper compares the performance of surface-related multiple elimination in the data and image spaces.

For this purpose, we use a 2D/4C real data set, acquired with an ocean-bottom cable in the Mahogany field, located in the Gulf of Mexico. The dataset provides an interesting test, because conventional multiple-removal methods fail. There is not enough difference between the moveout of primaries and multiples, and the water depth is relatively shallow, thus producing strong multiple reflections at deep targets.

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We first present a review of the theory behind multiple suppression by adaptive subtraction. Then, we present the results of multiple suppression both in the data space and in the image space. We conclude that multiple elimination in the image space yields a better final pre-stack image. However, the image space approach has a cost disadvantage, since a full migration of the multiple model is needed.

MULTIPLE ELIMINATION THEORY

The Delft approach (Verschuur et al., 1992) is able to remove surface-related multiples for any type of geology, as long as the receiver and source coverage at the surface is dense enough. One of the main advantages of the Delft method is that no subsurface information is required.

In this implementation of the Delft approach, we first create a kinematic model of the water-bottom multiple by convolving in time and space a water-bottom operator. We do this convolution such that the kinematics of all surface-related multiples are accurate. Then, the relative amplitudes of the first-order multiples are correct, but the amplitudes of higher-order multiples are over-predicted (Wang and Levin, 1994; Guitton et al., 2001).

Once a multiple model has been estimated, it is adaptively subtracted from the data. Note that, as pointed out by Berkhout and Verschuur (1997), this first subtraction step should be followed by more iterations. The goal of the iterative procedure is to better estimate and eliminate higher-order multiples (Verschuur and Berkhout, 1997). In this paper, we iterate only once and hope that the adaptive subtraction step is flexible enough to handle all the multiples at once.

We use non-stationary filtering technology for adaptive-subtraction (Rickett et al., 2001). The main advantage of these filters is that they are computed in the time domain and thus take the inherent non-stationarity of the multiples and the data into account. Therefore, it is possible to estimate adaptive filters locally that will give the best multiple attenuation result. Note that by estimating two-sided 2-D filters gives a lot of degrees of freedom for the matching of the multiple model to the real multiples in the data.

Thus, given a model of the multiples $\mathbf{M}$ and the data $\mathbf{d}$, we estimate a bank of non-stationary filters $\mathbf{f}$ such that

$$g(\mathbf{f}) = \|\mathbf{M}\mathbf{f} - \mathbf{d}\|^2 + \epsilon^2 \|\mathbf{R}\mathbf{f}\|^2 \tag{1}$$

is minimum. In equation (1), $\mathbf{R}$ is the Helix derivative (Claerbout, 1998) that smooths the filter coefficients across micro-patches (Crawley, 2000) and ϵ is a constant to be chosen *a-priori*. Note that $\mathbf{M}$ corresponds to the convolution with the model of the multiples $\mathbf{m}$ (Robinson and Treitel, 1980). Remember that this model of the multiples is obtained by convolving in space and time the input data:

$$\mathbf{m}(\omega) = \mathbf{d}(\omega) * \mathbf{wb}(\omega), \tag{2}$$

where $*$ defines the convolution process detailed in Verschuur et al. (1992), and $\mathbf{m}(\omega)$, $\mathbf{d}(\omega)$, and $\mathbf{wb}(\omega)$ are the multiples model, the data, and the water-bottom operator for one frequency

(ω), respectively. In equation (1), the filters are estimated iteratively with a conjugate-gradient method.

The Delft approach is widely used in the industry and is known to give currently the best multiple attenuation results for complex geology (Dragoset and Jericevic, 1998). However, it has been shown that this method suffers from an approximation made during the adaptive filtering step. For instance, when "significant" amplitude differences exist between the primaries and the multiples, the multiple model might be matched to the primaries and not to the multiples. A solution to this problem is using the ℓ^1 norm in equation (1) (Guitton and Verschuur, 2002). Another assumption made in equation (1) is that the signal has minimum energy. Spitz (1999) illustrates the shortcomings of this assumption and advocates that a pattern-based method is a better way of subtracting multiples from the data.

EXAMPLE

The data set that we use for our analysis corresponds to a 2D OBC experiment in the Gulf of Mexico, in the Mahogany field. Rosales and Guitton (2004) present the preprocessing for this data set. After combining the hydrophone and geophone components, we still have the multiples related to the water bottom. For this particular data set, we can consider the water bottom to be flat throughout the data (Herrenschmidt et al., 2001). Therefore, we can apply the Delft methodology to CMP gathers, for the elimination of the water-bottom multiples.

Multiples model

First, we need to obtain the multiples model. For this we create an operator that represents the reflection from the water surface to the water bottom and back (Figure 1) We obtain the operator from the data itself, by considering the watter bottom a flat surface. We begin by isolating the first arrival, we then upward continue the first arrival to the water surface level. Figure 2 shows the comparison of one gather of our multiples model with the data itself.

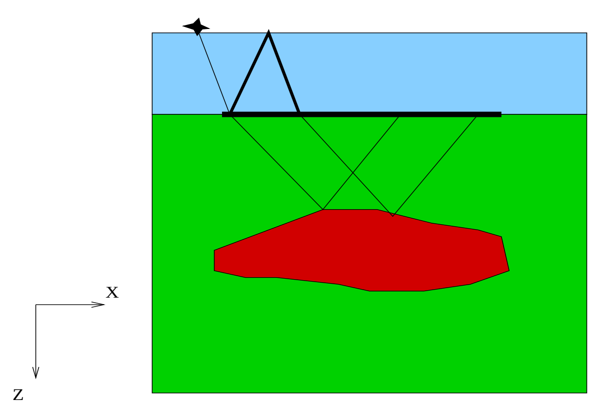

Figure 1: Multiple operator. An OBC acquisition with the source at the surface and the receivers at the bottom. For this shallow experiment the water-bottom multiple is the most dominant multiple. daniel3-sketch [NR]

The left side shows the multiples model and the right the data. Observe the good correlation between our data and the multiples model, not only at zero offset, but also in the moveout at far offset.

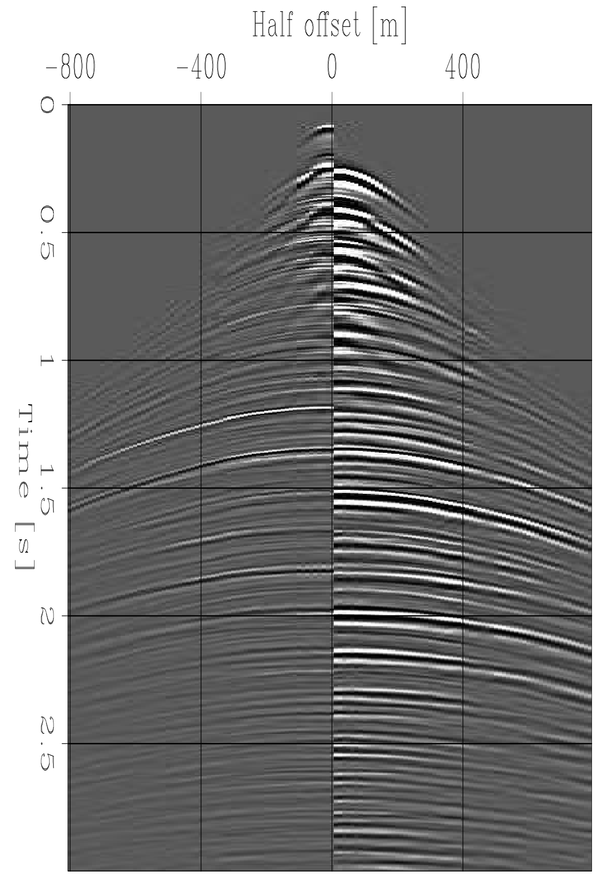

Figure 2: Multiples model compared against the data set. Left side corresponds to the data and right side to multiple model for the water-bottom. daniel3-mult.model [ER]

Data Space

We first applied adaptive subtraction to the Mahogany data set in data space. Since the water bottom is fairly shallow (approx. 118 m), the water-bottom multiples are the most dominant multiples in the data set. Figure 3 shows one CMP, between 2 s and 4 s. This figure shows, from top to bottom: A) the multiple model; B) the result of the adaptive subtraction, the estimated primaries; C) the filter obtained with the multiples model for performing the subtraction; and D) the original data set.

Many multiples were totally eliminated, while others where partially eliminated. The results are comparable throughout the data set. The shallow multiples, while they were partially eliminated, still retain some energy. As we will see in the next sections, this remaining energy will still interfere with an otherwise accurate final image.

Image Space

We now apply adaptive subtraction after migration. We perform split-step wavefield downward-continuation migration to go from the data to the image space. Both the original seismic data and the multiples model were migrated with the same algorithm. Because the velocity model is still an unknown at this stage of the processing, we use a simple, vertical-gradient velocity

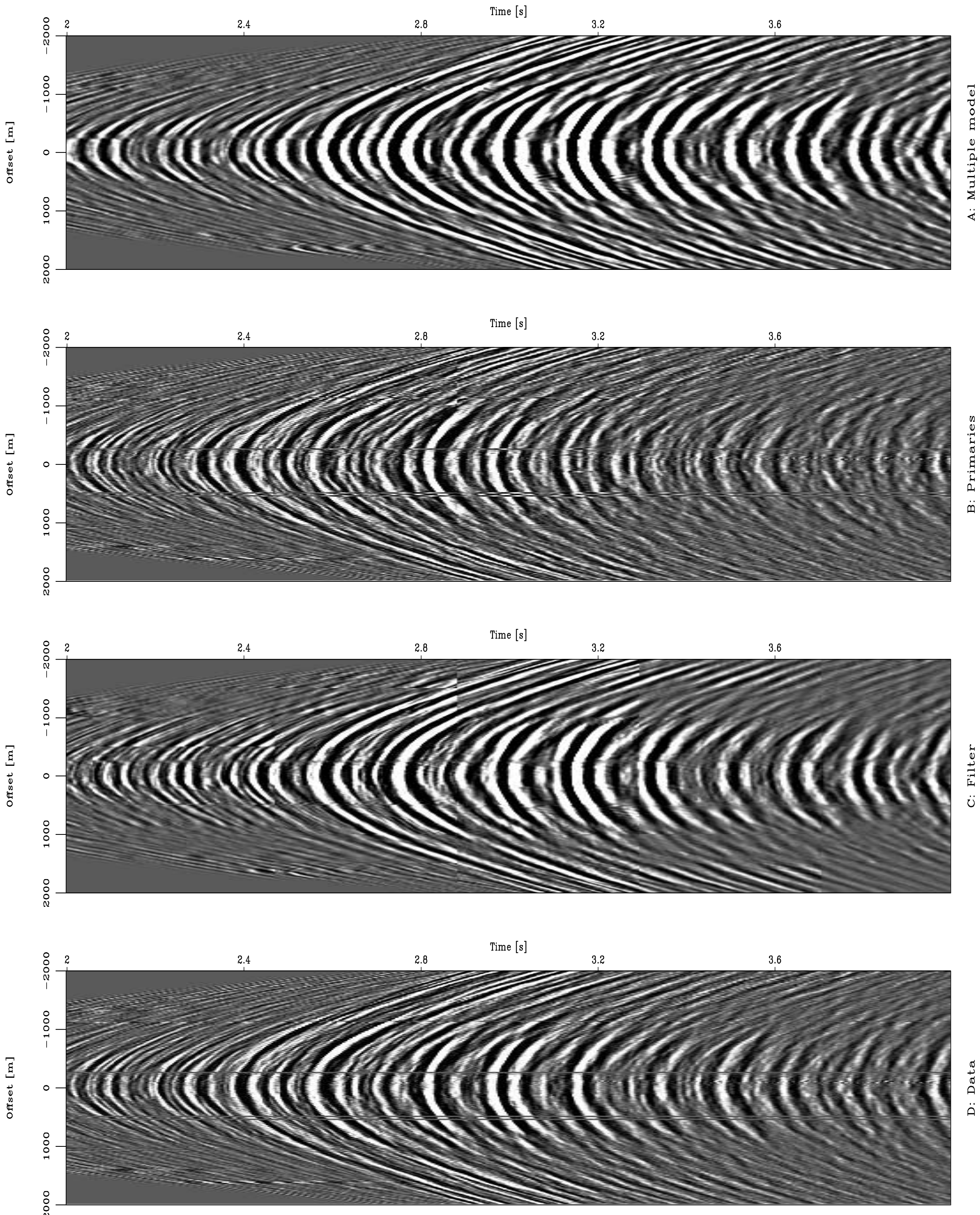

Figure 3: Data space multiple removal. From top to bottom: A) multiple model; B) Primaries; C) Filter; D) Data. daniel3-dspace_4panel [CR]

function. We use the same velocity model for the original data set and the multiples model. Since this particular data set corresponds to an OBC acquisition, both the original data set and the multiples model were re-datumed in order to have both sources and receivers at the same depth level before the migration.

Figure 4 shows one angle-domain common-image gather, following the same presentation scheme for the results in the data space. The figure shows, from top to bottom: A) the migrated multiples model; B) the result of adaptive subtraction in the image space, that is the primaries; C) the filter obtained with the migrated multiples model for performing the subtraction; and D) the migrated data set.

We first observe that both the migration of the entire data set and the migration of the multiples (panels A and D) have a residual curvature in the angle gathers because we have the correct velocity model. However, this is not an obstacle to performing the multiples subtraction in this domain, since both panels present the same residual moveout. After estimating the filter for performing the subtraction (panel C), we were able to eliminate almost all the multiples present in our multiples model.

Data space vs. Image space

To compare the results of multiple elimination in the data space directly to the multiple elimination in the image space, we transformed our data-space substraction results into the image space. Figure 5 compares the same angle-domain common-image gathers for multiple removal in the data space and in the image space. The figure shows, from top to bottom: A) the migrated multiples model; B) the result of adaptive subtraction done in the data space, after migration; C) the result of adaptive subtraction done in the image space; and D) the migrated data set.

We observe that the multiples eliminated in the data space are also eliminated in the image space. However, some multiples were eliminated better in the image space, as, for example, the strong multiple at around 2800 m. Figure 6 compares the stack of the data space and image space results: from top to bottom, we have: A) the migration stack of the primaries obtained from the adaptive subtraction in the image space; B) the migration stack of the primaries obtained from the adaptive subtraction in the data space; and C) the migration stack of the original data set. Figure 7 compares the stack of migrated multiples models. From top to bottom, we have: A) the migrated multiple model; B) the estimated multiple section from the processing in the data space; and C) the estimated multiple section from the processing in the image space.

DISCUSSION AND CONCLUSIONS

Multiples are not always easy to eliminate with well-known methodologies, and many times we carry them into the imaging process. During velocity analysis, multiples interfere destructively with velocity model building. At this stage, primaries and multiples both have residual

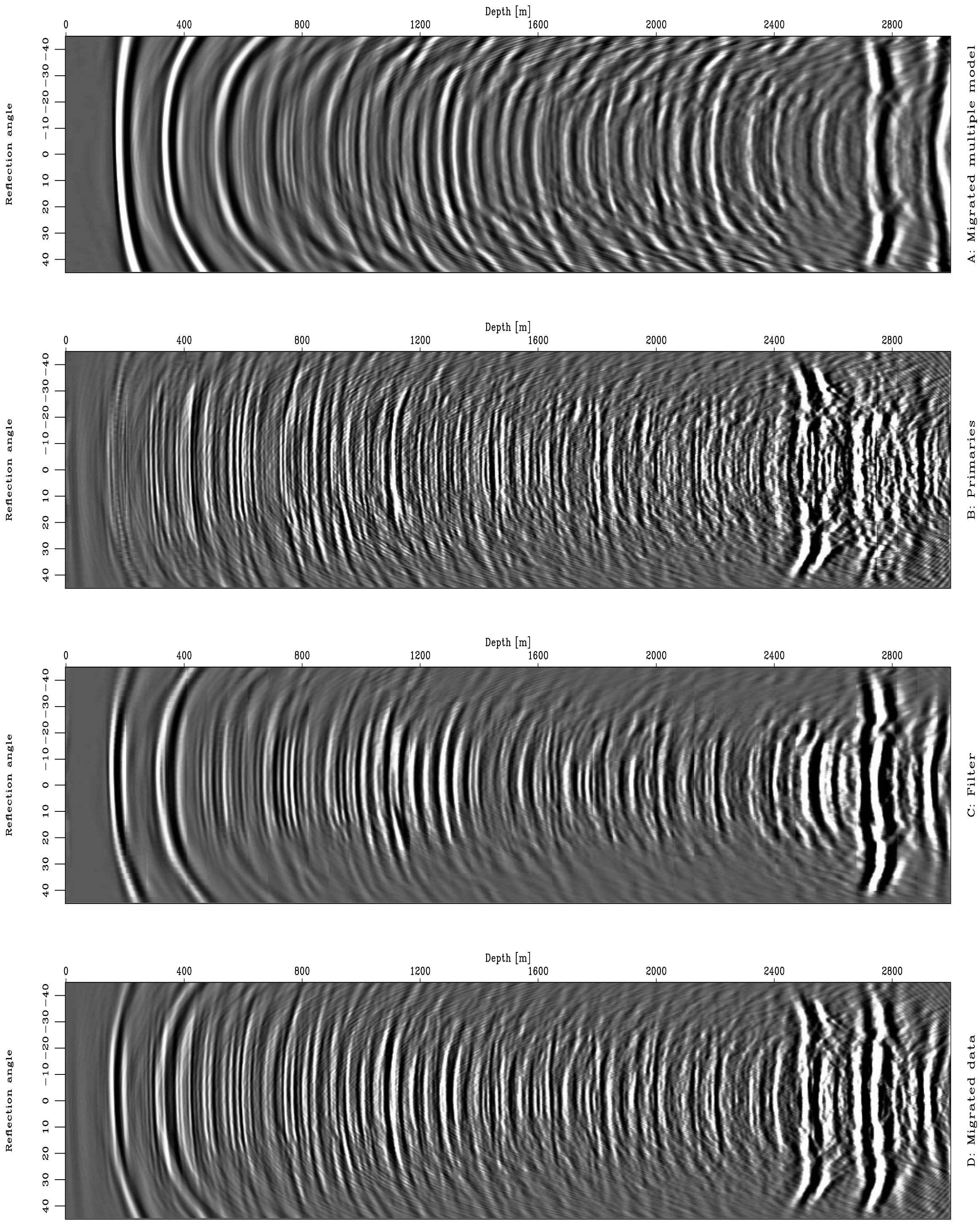

Figure 4: Image space multiple removal. From top to bottom: A) Migrated multiple model; B) Primaries; C) Filter; D) Migrated data. daniel3-ispace_4panel [CR]

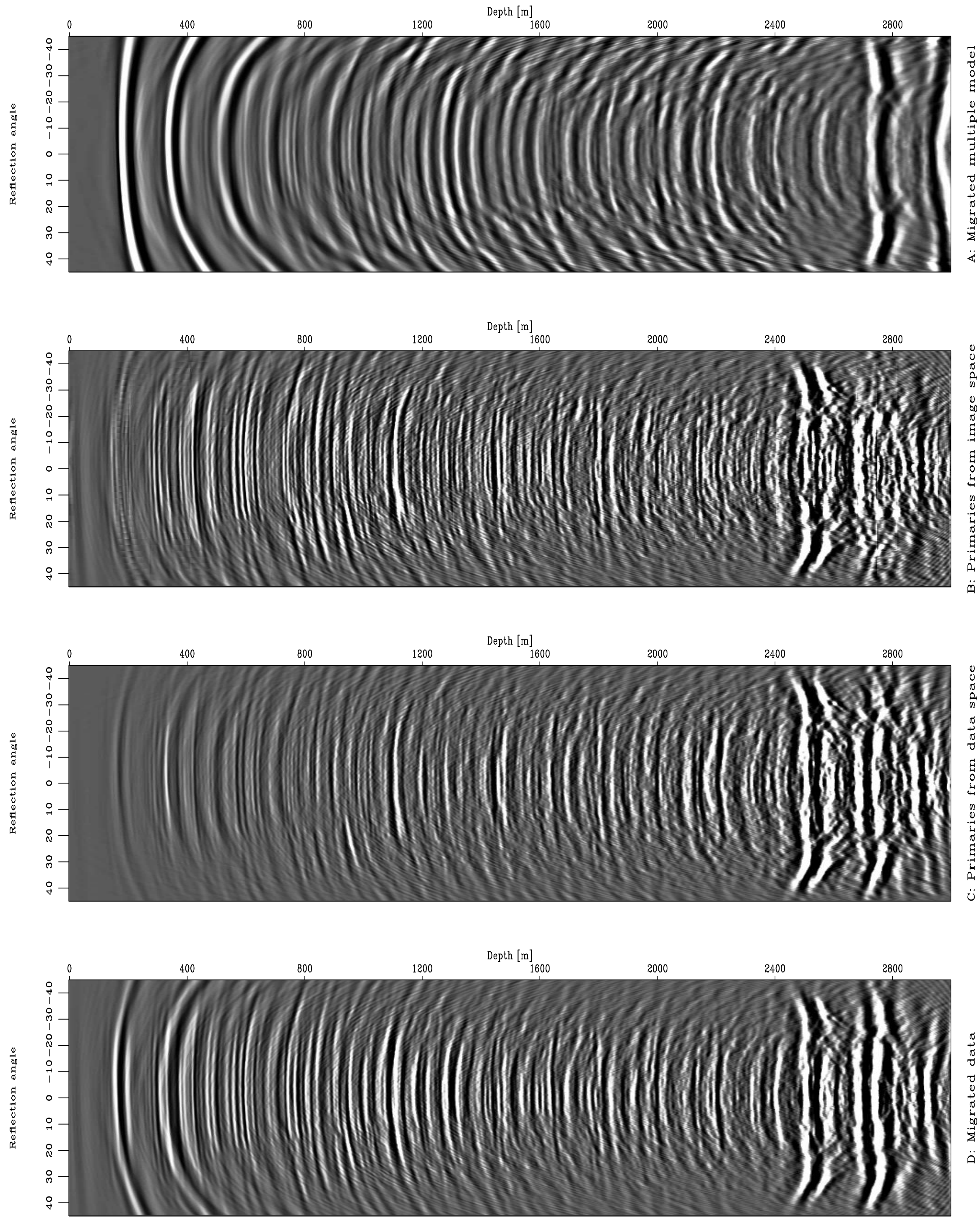

Figure 5: Comparison between multiple removal in the data space versus the image space. From top to bottom: A) Migrated multiple model; B) Primaries from the data space; C) Primaries from the image space; D) Migrated data. daniel3-ispace_dspace [CR]

moveouts that do not allow for a separation and elimination.

The shallow multiples are better eliminated in the image space. Since there is a very small coverage in offset for these multiples, when transformed to the image space and mapped into angle-domain common-image gathers, there is a wider distribution along the angle axis in the image space compared with the offset axis in the data space; therefore, subtraction performs better in the image space than in the data space.

For deeper multiples, although we were able to do a good job in the data space, there is still some energy remaining. The coherent noise is strong enough to produce an event in the image space that might interfere with future processing, such as, migration velocity analysis. Although, more detailed work can always be done in the data space to remove the multiples more carefully, the final stage and result are going to be in the image space. If we see coherent noise in the image space, we will be obligated to go back to the data space and re-process the data.

This re-processing is not needed if we do all our processing in the image space. The image space is where we want our final result to be coherent and interpretable. Furthermore, it is ideal for performing target-oriented processing and/or analysis, as, for example, focusing on an specific event or area to improve the image, like velocity or illumination problems.

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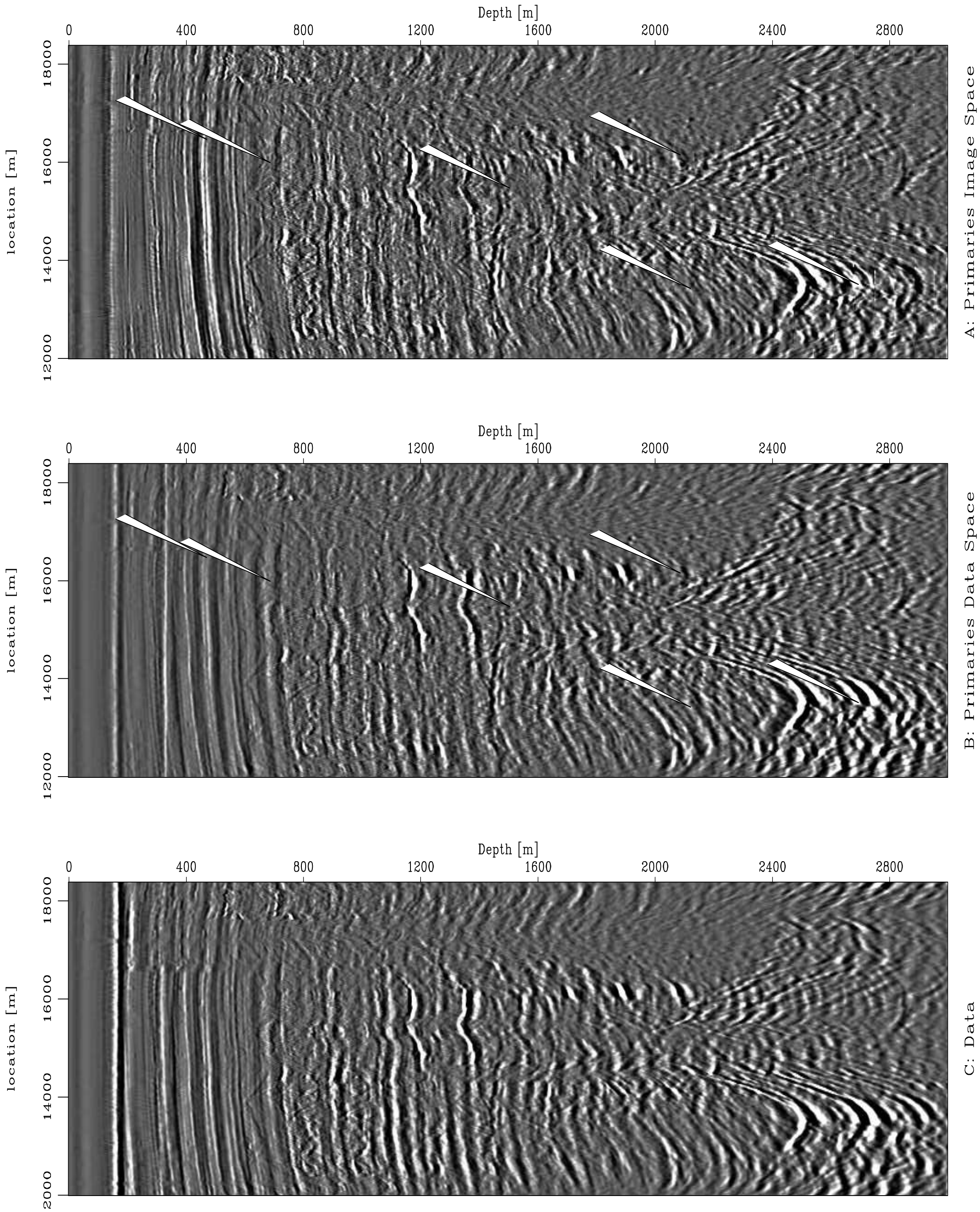

Figure 6: Comparison between multiple removal in the data space versus the image space. From top to bottom: A) Migrated stack of primaries from the image space processing; B) Migrated stack of the primaries from the data space processing; and C) Migrated stack of the entire data set. daniel3-is_ds_stack [CR]

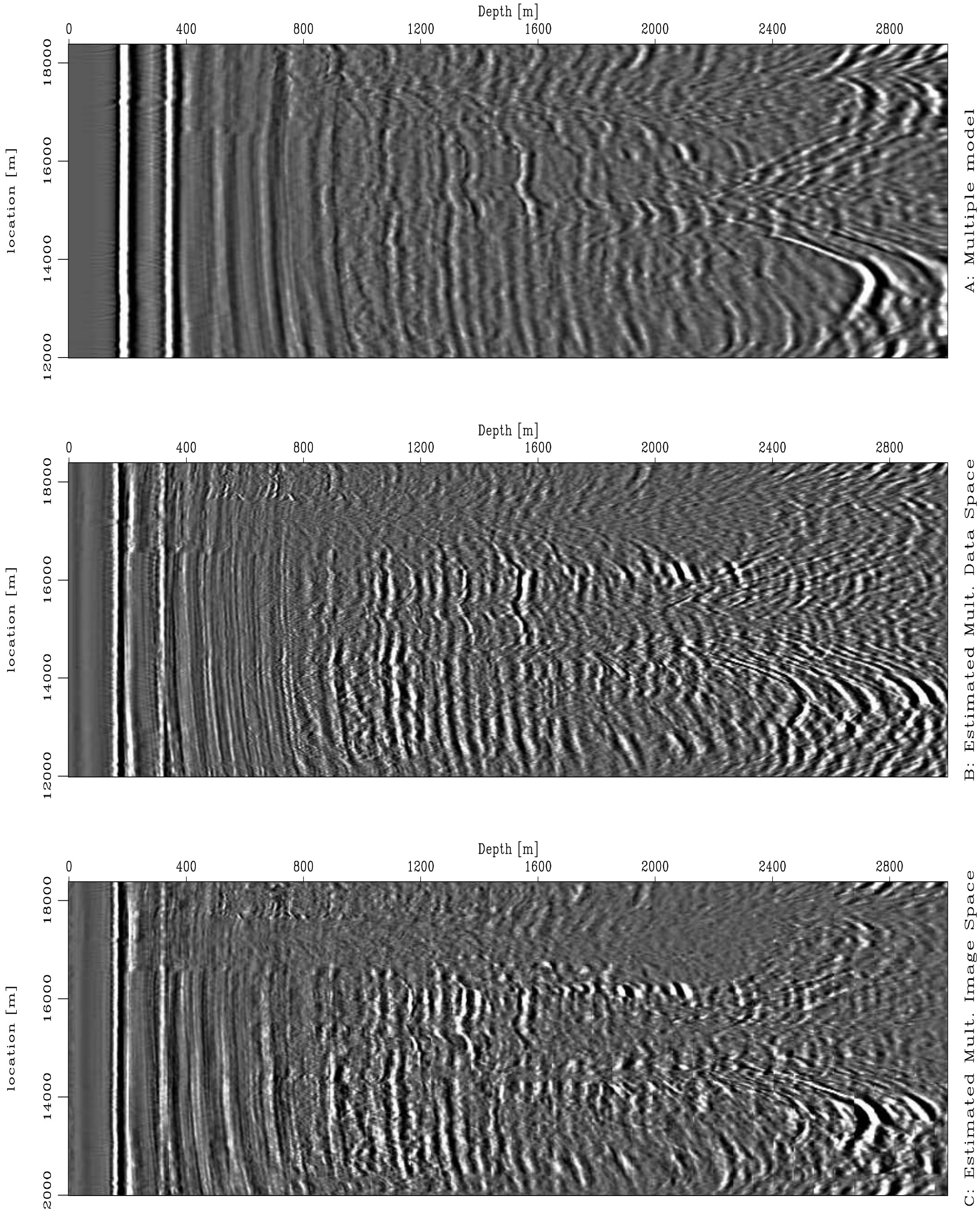

Figure 7: Comparison between multiple removal in the data space versus the image space. From top to bottom: A) Migrated stack of the multiple model; B) Estimated multiple section from the data space processing; and C) Estimated multiple section from the image space processing. daniel3-is_ds_mult [CR]