A 3D methodology for residual and diffracted multiple attenuation

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Summary

Demultiple techniques such as 3D SRME and 3D wave equation modelling are able to model complex surface related multiples to a good extent, particularly in terms of their kinematics. However, the high frequency contents in the multiples model are often lacking due to stacking and/or convolutional operations. In addition, out-of-plane diffracted multiples are usually inadequately modelled by these techniques due to coarse streamer sampling. All these factors contribute in lowering the quality of any multiples model. Hence the demultiple process is not sufficient and some residual multiples are left in the data. These multiples would require further attenuation by a post demultiple process.

This abstract proposes a novel post demultiple solution to attenuate both residual and diffracted multiples. The solution incorporates three main physical attributes that can be used to discriminate between primaries and residual multiples in moderate to deep water surveys: (i) amplitude range, (ii) frequency content and (iii) dip content. The proposed solution can be seen as a 3D frequency and dip dependent de-spiking process with Fourier based reconstruction to preserve primary signal.

Introduction

Diffracted and residual multiples are a major problem in some geological regimes which are characterized by rough water bottom topology and/or complex sub-seabed geology. They contaminate the deeper parts of the seismic section (starting from twice the water-bottom time) and may overlap with primary energy. An example of a subline section from a near offset seismic volume with visible residual multiples is shown in Figure 3. The need to remove these residual multiples before migration is important in order to avoid reducing the resolution of the subsurface image.

Parabolic Radon demultiple is routinely used as a post demultiple process to remove residual multiples. However, this process is only effective in the mid to far offset range, where move-out discrimination between primaries and multiples is possible. As for the out-of-plane diffracted multiples, they can have an approximate hyperbolic move-out in the CMP domain with an apex shifted from zero-offset. Modified Radon demultiple techniques can then be used in this case (Hargreaves *et al*., 2003); however this approach is relatively expensive and may distort primaries (Abma *et al*. 2002).

In practice, customized noise attenuation approach is used to remove residual and diffracted multiples, which are considered as a broadband random noise (Brittan *et al*. 2004). Bekara et al. (2011) proposed a solution that falls into this category. This solution is equivalent to a data-adaptive and time-space varying high-cut filter that targets and filters out incoherent high-amplitude samples from the data using predictive error filters (Canales 1984). However this solution reaches its limitation when the residual multiples are coherent or when there is large spectral overlap between primaries and multiples. In these cases, a “remove and reconstruct” approach would be more appropriate than a denoise approach.

This abstract proposes an extension to the solution mentioned above in an attempt to address its limitations. The novelty can be summarized in the following points:

1. Dip discrimination: in addition to frequency and amplitude, dip is used to improve the localization of the residual/diffracted multiples
2. Consistent noise detection: noise detection is done upfront and is separated form noise filtering
3. 3D Fourier reconstruction is used to fill in the noisy samples

The first point introduces an additional physical attribute that can be used to discriminate between residual multiples and primaries, hence localization of residual multiples is improved. The second point, while it comes with a computational overhead, improves the robustness of residual multiples detection. The issue with combined detection and filtering in the same processing window is window to window consistency. The third point allows the solution to remove residual multiples that have a large spectral overlap, mainly toward low frequencies, with primaries underneath them.

Methodology

1. Assumptions

The proposed method is based on the assumption that diffracted and residual multiples have higher amplitudes, higher frequencies and optionally higher dip content compared to any primary at the target time of application. This assumption comes from the physical fact that absorption of amplitude and frequency is larger for primaries as they propagate through the subsurface, compared to diffracted/residual multiples where most of their propagation path is through the weakly absorbing water layer. This assumption is more significant in deep to mid water depth surveys and gets less exact as we move to shallower water. After NMO correction, the residual

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multiples and particularly diffracted multiples will have a steeper dip compared to primaries.

2. Description

The main idea of the methodology is to separate the data into two parts. The first part, called the detection data, is a filtered version of the input data that contains the high frequencies and the steeper dip events. Here, we assume that the detection data is mainly dominated by the residual multiples and will be used later for the detection. The second part, called the preserved data, is also a filtered version of the input data that contains the low frequency and flatter events in the data. We assume that the preserved data contains only primaries. The detection data is analyzed to determine the location of residual multiples samples, which are referred to as noise samples. The purpose of the detection data is to construct a mask to protect primaries and to localize noise. The preserved data is left untouched. The noisy samples in the unpreserved part of the data are completely removed and interpolated using 3D Fourier reconstruction. A flowchart of the process (2D case for illustration) is shown in Figure 1.

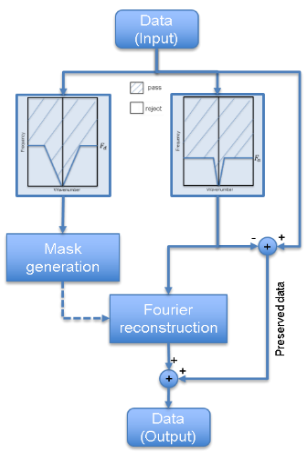

Figure 1. Flowchart diagram of the proposed method

3. 3D Fourier reconstruction

The 3D Fourier reconstruction works on local 3D time-space windows that slide with an overlap to cover the entire data volume. The process fills-in "holes" in the volumetric window, where the holes are the locations of noisy samples. Let $d_0(t,x,y)$ denote the input windowed data with hole, where $t \le t_m$, $x \le x_m$ and $y \le y_m$. We define $L_N = \{(t_i,x_i,y_i)\}_{i=1,..N}$ as the locations of the N holes, *i.e.* $d_0(L_N) = \mathbf{0}$ and L_S as the locations of the signal samples. The proposed reconstruction belongs to the family of POCS algorithms (Projection Onto Convex Sets), which are widely used in seismic applications (Abma et al, 2006). The pseudo-code for the proposed 3D Fourier reconstruction is as follows:

Fourier reconstruction algorithm

1. $D_{it}(f,k_x,k_y) = 3DFFT(d_{it}(t,x,y))$
2. $D_{it}(f,k_x,k_y) = 0$ if $\lvert D_{it}(f,k_x,k_y)\rvert \le T(it)$
3. $d_{it+1}(t,x,y) = \text{3DIFFT}\left(D_{it}(f,k_x,k_y)\right)$
4. $d_{it+1}(L_S) = d_0(L_S)$
5. $d_{it+1}(t,x,y) = 0$ if $(t > t_m)$ or $(x > x_m)$ or $(y > y_m)$
6. *If ($\lvert d_{it+1} - d_{it}\rvert < \varepsilon$) exit, else go to 1*

The basic idea behind this algorithm is a sparsity promotion on the estimated data (step 2), while ensuring that the solution lives in a constrained set (step 4 and 5). For example, step 4 is a projection onto the set of all solutions with known values for the non-noisy samples. A key parameter of this process is the threshold $T(it)$ used in step 2 and it should decrease with iterations. The compromise is simple, a fast decrease of the threshold will give a sub-optimal solution in the sense that the reconstructed samples will have weak amplitudes as the final solution doesn't move away from the initial solution of zero. A slow decrease is desirable, but at the cost of increasing run time.

Figure 2 shows an example of 2D Fourier reconstruction applied on a small seismic window (1.0s x 200 traces). Visually the regeneration of events looks good and the spectral analysis shows that this reconstruction works better for low frequencies up to 40Hz and after that a clear denoise effect is visible (Figure 3). This is fine for our application, as the objective is to reconstruct the distorted primaries that are underneath or near the residual multiples and which tend to have a low frequency content.

Data Examples

Figure 4 shows a subline section from a near offset volume that is contaminated by heavy residual and diffracted multiples. The complex geology and a difficult near offset extrapolation, which is needed for the multiple modeling, are the main reasons for this high level of residual multiples. The result of applying the proposed method to the same section, with Fourier reconstruction as low as 10 Hz is shown in Figure 5. Overall, a good proportion of residual multiples is removed without a visible seam at twice WBT. In this example, the frequency discrimination was enough to achieve an acceptable result. To further assess the impact of

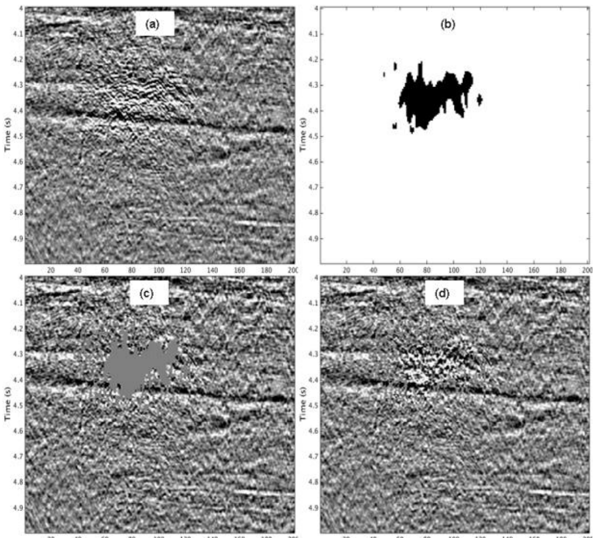

Figure 2. Example of Fourier data reconstruction. (a) Input data with residual multiples, (b) noise mask, (c) input to the Fourier reconstruction algorithm, (d) output of the Fourier reconstruction algorithm

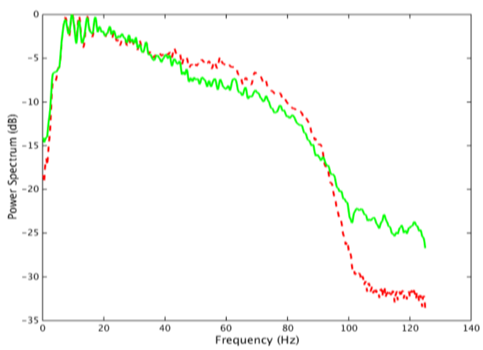

Figure 3. Amplitude spectra, (---) of the data in Figure (2-a) before the Fourier reconstruction, (—) of the data in Figure (2-d) after the Fourier reconstruction

Fourier reconstruction and the use of dip to discriminate between primaries and multiples, we compare the proposed method with the method in Bekara et al, 2010 which is 2D and uses prediction error filtering to attenuate multiples. Figure 6 displays a zoomed window from the input data as indicated by the rectangle in Figure 4. It shows clearly some low frequency primaries masked by residual multiples. The application of the 2D process was done with 2 cascaded passes (subline and then crossline). Its parameterization was made exceptionally harsh in order to match the same harshness of the proposed 3D method. Figure 7 shows the output and the difference sections after the application of the 2D solution. Compared with the output of the proposed method (Figure 8-a), we can see little difference, except the

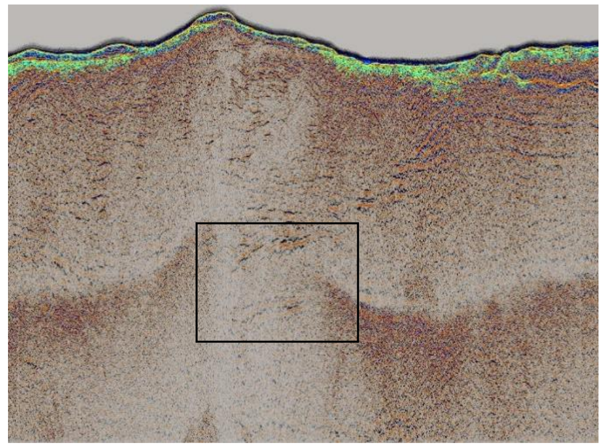

Figure 4. Subline section from a near offset plane (1275 m) with visible residual and diffracted multiples

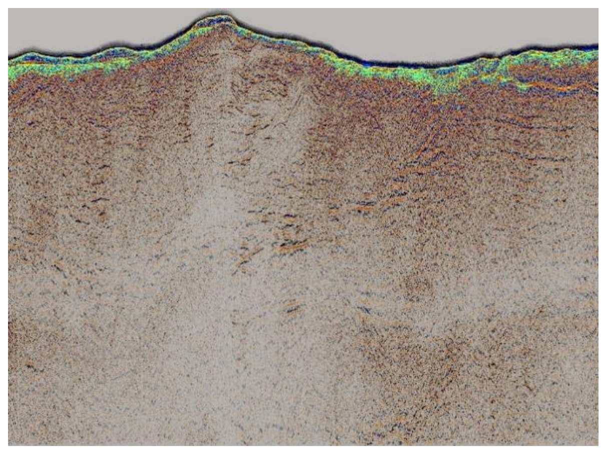

Figure 5. The same subline as in Figure 3 after the application of the proposed method

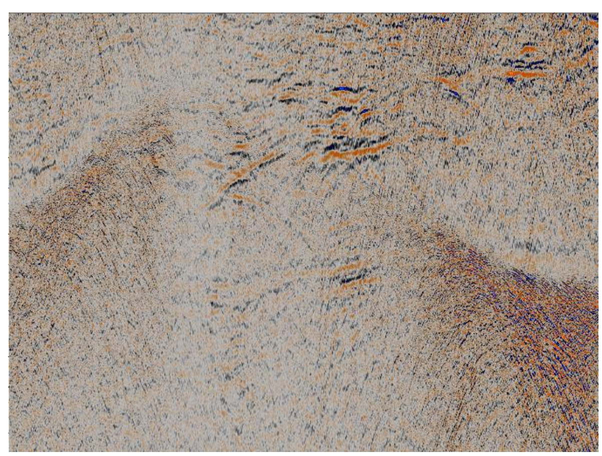

Figure 6. Zoomed section from Figure 4

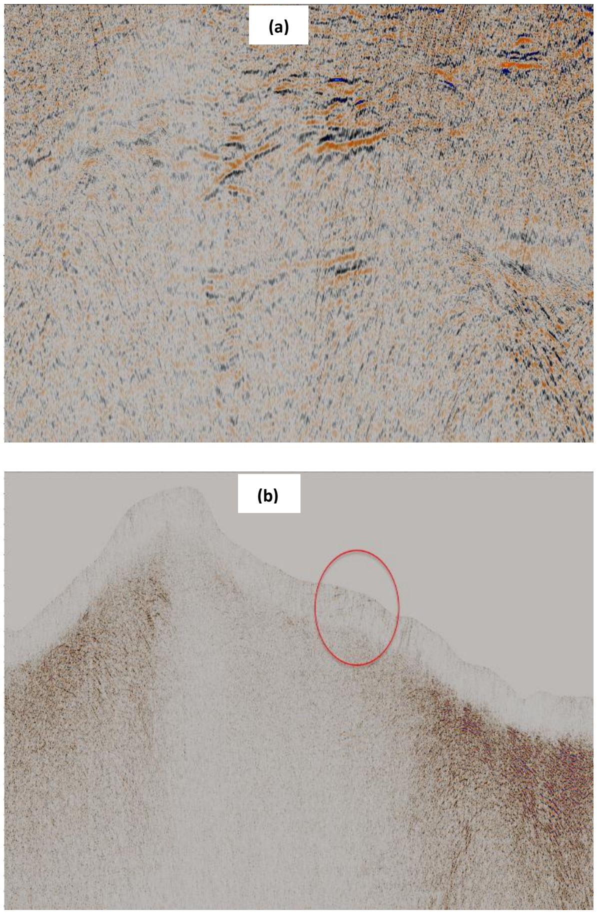

Figure 7. Zoomed section after application of 2D solution (a) Output, (b) Difference section

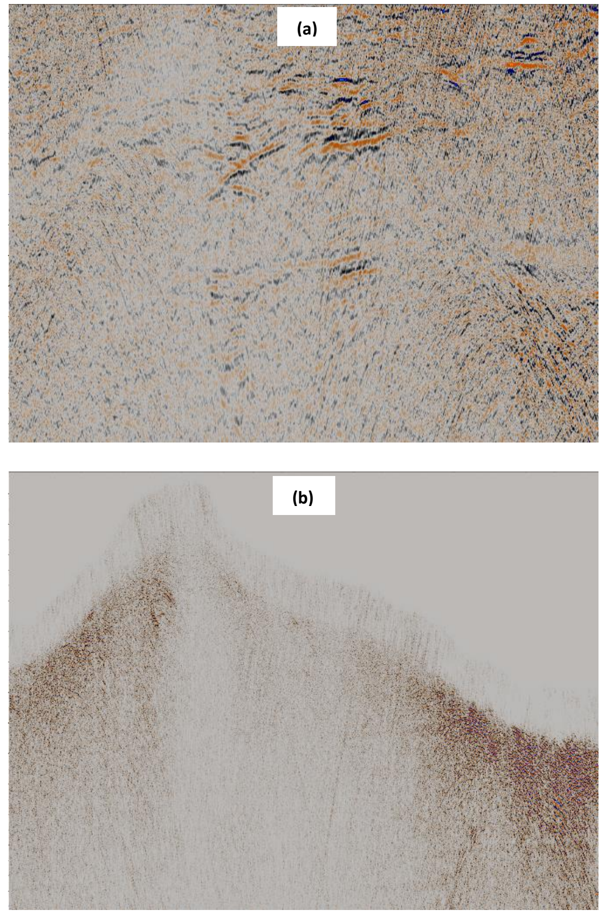

Figure 8. Zoomed section after application of proposed method (a) Output, (b) Difference section

seam is slightly more visible on the output of the 2D solution (Figure 7-a). Inspection of the difference sections, reveals that some primary leakage is observed after applying the 2D solution as indicated by a red circle in Figure 7-b. The effect of dip filtering is also visible with the proposed method (Figure 8-b), as tails of weak diffracted multiples are removed. Overall, on this dataset the 2D solution did not fail completely as the differences between the two methods are not huge. However, the proposed method is not only more signal-friendly, but also more efficient from the point of view of production management.

Conclusions

Residual multiple attenuation is a challenging problem in many processing projects. Amplitude, frequency and dip contents are useful attributes to discriminate between primaries and residual multiples. These attributes can be incorporated in the design of a time and space varying high-frequency, high-dip cut-filter that targets and removes the noisy samples related to residual multiples. The ability to attenuate noisy samples and reconstruct them using Fourier based POCS algorithm will give the user additional flexibility to lower the preservation frequency even further to tackle the low frequency part of the residual multiples. Moving to 3D gave advantage in both the detection and reconstruction. However, it comes at the cost of more CPU time.

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REFERENCES

Abma, R, N., Kabir, K., Matson, S., Shaw, B., McLain, and S., Michell, 2002, Comparisons of adaptive subtraction techniques for multiple attenuation: 72nd Annual International Meeting, SEG, Expanded Abstracts, 2186–2189, doi: https://doi.org/10.1190/1.1817141.

Abma, R., and N., Kabir, 2006, 3D interpolation of irregular data with a POCS algorithm: Geophysics, **71**, no. 6, E91–E97, doi: https://doi.org/10.1190/1.2356088.

Bekara, M., M., Sedhom, and A., Vigner, 2010, Methodology for diffracted multiple reduction: 72nd Annual International Conference and Exhibition, EAGE, Extended Abstracts, P417, doi: https://doi.org/10.3997/2214-4609.201401265.

Brittan, J., and A., Wrench, 2004, Attenuation of multiple diffractions using a cascaded noise removal sequence: First Break, **22**, 71–74.

Canales, L, 1984, Random noise reduction: 54th Annual International Meeting, SEG, Expanded Abstracts, 525–527, doi: https://doi.org/10.1190/1.1894168.

Hargreaves, N., B., verWest, R., Wombell, and D., Trad, 2003, Multiple attenuation using an apex-shifted Radon transform: 73nd Annual International Meeting, SEG, Expanded Abstracts, 1929–1932, doi: https://doi.org/10.1190/1.1817699.

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