From SRME or wave-equation extrapolation to SRME and wave-equation extrapolation

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Summary

Better de-multiple results are achieved by combining the strengths of SRME and wave field extrapolation techniques. In this paper, we illustrated three different techniques to attack this task. Among the three techniques, hybrid adaptive subtraction takes full advantage of the two multiple prediction techniques, and emerges as champion.

Introduction

Practically 3D surface related multiple removal involves two main steps. Firstly the surface related multiples are predicted. Secondly, the predicted multiple are adaptively subtracted from the original input.

For 3D multiple prediction, 3D surface related multiple elimination (SRME) and wave field extrapolation (WFE) are most common used approaches. SRME (Vercschuur et al 1992) is a data driven approach. It is based on a simple and powerful concept, convolving two traces with common bounce points at the free surface, will be able to generate the multiple related to this surface point. It can predict all surface-related multiples. WFE (Pica et. al. 2005) is essentially the reverse the wave equation migration. Multiples are predicted from modeling with the velocity model and seismic migration image (reflectivity model).

SRME and WFE each have pros and cons. SRME does not require any subsurface geology information; but it has strict requirement for the fully surface spatial sampling, source signature, and surface reflectivity. Constrained by the acquisition design, there are many factors that could lead to the quality of the SRME results, such as

- 1. Aliased shot spacing, narrow spread for NAZ data;
- 2. Cable feathering;
- 3. Wide cable spacing;
- 4.Limited length of cable;
- 5. Missing near offset data;

Some of the issues, item 2 and item 3, can be partly addressed by advanced data regularization/interpolation (Cai et al 2009). Some can be partially addressed by data extrapolation, such as item 5. But others may not be easy to solve. Particularly for complex 3D structure, the interpolated data will never be as good as real data. Also inside the SRME, to compensate the small offset difference between the offset bin and the actual offset, normally partial NMO is applied; these will introduce some errors as well. The error is not only introduced by the NMO local flat layers assumption, but also there is not a perfect

solution for NMO velocity to be able to handle both

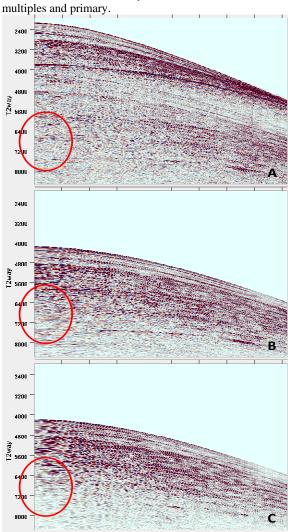


Figure 1: (A) Input shot, near cable. (B) SRME predicted multiples. (C) WFE predicted multiples.

Helped by the additional information from reflectivity model, WFE has looser restriction on the surface spatial sampling than SRME. For shot domain implement, WFE does not need shot interpolation. But data interpolation within the shot will help to improve the predicted multiple's quality (Cai et al, 2009). The key component for the quality (both kinematic and dynamic) of the multiple

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prediction is the reflectivity model. Even though the velocity model is one of the important components, but since WFE essentially is a de-migration processing combining with migrated imaging, as long as the velocity field is consistent, we found the velocity is not as crucial as reflectivity model (migration imaging).

From computation point of view, WFE is very suitable for wide-azimuth data (WAZ) because it implements shot by shot a wave-equation modeling operation. The main factor that determines the computation is the shot coverage area not the number of traces. SRME on other hand, is implemented trace by trace, so the number of trace determines the total computation cost.

We propose to combine SRME and WFE to overcome their individual weakness. There are many things that we can do on this prospect; here we demonstrate three possibilities mainly at the adaptive subtraction stage.

Methodology and Algorithm

The examples from TGS' Freedom WAZ survey are used to demonstrate the concept and algorithm. Figure 1 shows one of the near cable for the input shot (Figure 1A), SRME predicted multiples (Figure 1B), and WFE predicted multiples (Figure 1C). From Figure 1, we can see overall SRME predicted multiples did a better job, while at the near-offset deep portion, it is slight under estimated caused by lack of data coverage for the near offsets. WFE did a better job at the near-offset below 5500ms, partly benefited from our high fidelity near-offset extrapolation, partly benefited from the additional information from reflectivity model.

The SRME and WFE adaptive subtraction results are shown in Figure 2. As expected, the SRME adaptive subtraction attenuated most of the multiples, particular for the middle to far offset high frequency multiples. WFE did a better job at the near-offset below 5500ms. Now the question is can we combine these two results? The answer is yes, we will give three methods to achieve the goal.

Methodology I: SRME+WFE

The simplest and most straight method is summing the SRME predict multiples with WFE predicted multiples, then run adaptive subtraction. We call it SRME+WFE technique. SRME and WFE were adapted to the input data in the global sense respectively to compensate the dynamic difference before summing together. The subtraction result is shown in Figure 3. Overall the subtraction result is better than WFE subtraction results (Figure 2B), but worse than SRME subtraction results (Figure 2A).

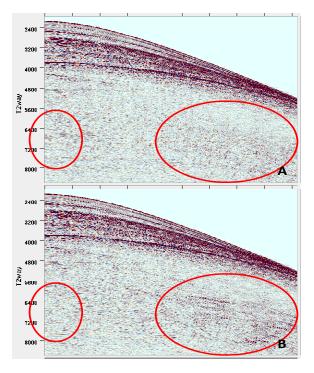


Figure 2: Adaptive subtraction results. (A) SRME. (B) WFE.

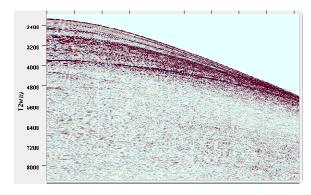


Figure 3: SRME+WFE subtraction results.

Methodology II: SRME2WFE

The second technique is to adapt SRME predicted multiples to WFE predicted multiples. We call it SRME2WFE technique. There is a practical reason to do so. Theoretically SRME defined as $M = \sum_{aperture} F \bullet D \otimes P$

$$M = \sum_{\text{exercises}} F \bullet D \otimes F$$

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where D is input data. P is the multiple free primary. F is the filter to correct the phase and amplitude distortion caused by sparse spatial sampling of input data.

Practically to make the algorithm more efficient, we often implement it in one pass instead of multiple passes, and calculate the multiple as input data convolved with itself within the user define aperture

$$M = \sum_{aperture} F \bullet D \otimes D$$

The predicted multiples will have right kinematic but not dynamic/amplitude, particular for high order multiples. For WFE, the amplitude for the higher order multiples are mainly determined by the reflectivity model. If the reflectivity model is correct, it will be closer than the SRME's prediction for high order multiples. A mild matching filter is implemented to match SRME to WFE, which will make the amplitude correction for SRME high order multiples prediction. The SRME2WFE subtraction results (Figure 4) is very close to SRME subtraction results, which have potential to be better if there is a crossing events between the primary and high order multiples. In some places the subtraction did a little too much.

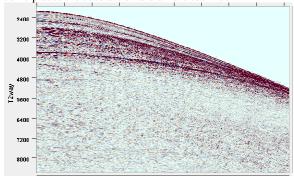


Figure 4: SRME2WFE subtraction results.

Methodology III: Hybrid adaptive subtraction

The task for adaptive subtraction is to derive a nonstationary filter f that minimizes the objective function

$$g(f) = ||D - M \otimes f||^2$$

where D is the input data, M is the SRME or WFE predicted multiple model. \otimes is convolution. The filter is estimated in least-square sense for one shot gather at a time. The residual $D-M\otimes f$ contains the estimated primaries.

For SRME predicted multiple model, the adaptive subtraction is

$$g_{SRME}(f_{SRME}) = ||D - M_{SRME} \otimes f_{SRME}||^2$$

For WFE predicted multiple model, the adaptive subtraction is

$$g_{\it WFE}(f_{\it WFE}) = \left\| D - M_{\it WFE} \otimes f_{\it WFE} \right\|^2$$
 We can formulate the adaptive subtraction as

$$g(f) = \min \left[g_{SRME}(f_{SRME}) \parallel g_{WFE}(f_{WFE}) \right]$$

Practically, for each of the time and trace window, we will perform the subtractions for both SRME predicted multiple model and WFE predicted multiple model. Then select one with the less energy as the final results. We call it hybrid adaptive subtraction.

The hybrid subtraction result is shown in Figure 5 combines the strength of both SRME and WFE, and provides the best results. The near-offset deep portion multiples are better attenuated than SRME results, middle to far offset multiples are well attenuated than WFE results. Also around the 4s, the primaries are preserved.

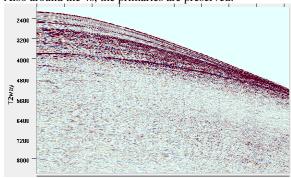


Figure 5: Hybrid subtraction results.

Figure 6 to Figure 11 show the near-offset stack for near cables. Again we can see the multiple reject quality from low to high is SRME+WFE to SRME2WFE to hybrid adaptive subtraction.

Conclusion

The SRME and WFE each has its pros and cons. We could combine their strengths to overcome their weaknesses at the adaptive subtraction stage. Three techniques are illustrated in this paper. Among the three techniques, the hybrid adaptive subtraction gives the best result.

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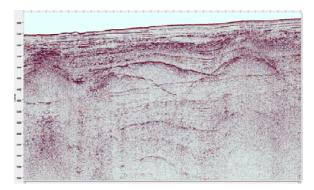


Figure 6: Input stack for near cable near-offset.

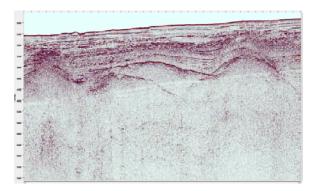


Figure 7: SRME adaptive subtraction stack for near cable and near-offset.

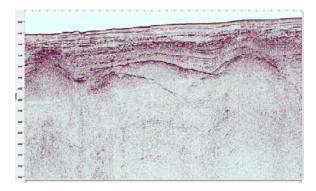


Figure 8: WFE adaptive subtraction stack for near cable and near-offset.

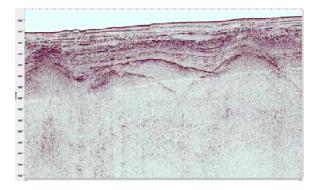


Figure 9: SRME+WFE adaptive subtraction stack for near cable and near-offset.

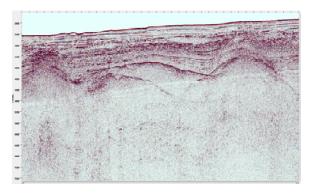


Figure 10: SRME2WFE adaptive subtraction stack for near cable and near-offset.

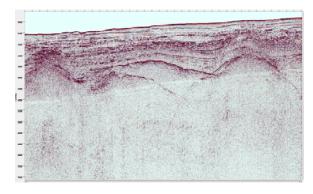


Figure 11: Hybrid adaptive subtraction stack for near cable and near-offset.

EDITED REFERENCES

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