# A MULTIPLE SUPPRESSION METHOD VIA CRS ATTRIBUTES, UPDATED

S. Dümmong, D. Gajewski, and C. Hübscher

email: stefan.duemmong@zmaw.de keywords: Multiple suppression, CRS-workflow, Imaging

## ABSTRACT

Multiple identification and attenuation are one of the most challenging tasks in the seismic data processing chain. We are presenting an continued approach for the identification of surface related multiples within the Common Reflection Surface (CRS) workflow, so that a processing chain from time to depth imaging with CRS related technology can be established. The approach assumes hyperbolic moveout of the multiples and is based on multiple prediction by auto-convolving each stacked trace. This involves a 1d approximation leading to prediction errors. Therefore a correction algorithm was implemented, which is based on a normalized 2d cross correlation function to determine a correction term for the multiple prediction. The process is similar to an image comparison problem and can be applied in a windowed way to correct for differential errors. After the multiples are identified / predicted prestack seismograms are calculated with the help of the CRS attributes and adaptively subtracted from the prestack data. Tests were performed on a real marine data set, which indicate the potential of this method. The identified / predicted multiples were successfully removed from the data set.

## INTRODUCTION

As already mentioned in last years WIT report, the CRS-workflow (Hertweck et al., 2003) is a powerful tool for a stable and quick processing chain from time to depth imaging. Currently it consists of the Common Reflection Surface (CRS) stack (Mann, 2002), the Normal Incidence Point (NIP) wave tomography (Duveneck and Hubral, 2002), and a corresponding post- or prestack depth migration algorithm. One of the facts that hampers the application of this workflow are multiples present in the data. Initial approaches to adress these within the CRS-workflow were presented by Gamboa et al. (2003) and Dümmong and Gajewski (2007). The latter one is expanded in this paper.

Available methods for multiple suppression are the Surface Related Multiple Elimination (SRME) method after Verschuur et al. (1992), the inverse scattering series after Wegelein et al. (1997), and the hyperbolic radon transform, see for example Ryo (1982). For shallow water environments the predictive deconvolution is also widely used. All of these methods have their advantages and disadvantages, for several reason. Non of these methods could be directly included into the CRS-workflow due to additional requirements, like regularization of the data, wavelet knowledge, manual picking, etc. Here an alternative approach is addressed for directly incorporating multiple suppression into the CRS-worflow.

The approach of multiple suppression with CRS attributes is based on the work of Kelamis and Verschuur (1996). The basic idea is that the auto-convolution of a seismic trace with itself predicts multiple reflections. This concept is applied in the high signal to noise ratio CRS stack data domain and provides a direct prediction of the ZO traveltimes of the multiples. Due to the 1d approximation in this process, prediction errors are inherent. To reduce the prediction errors a correction term based on an image matching process is introduced. The predicted multiples are corrected in time and space to match the original multiples on the stacked section, as close as possible.

After detecting the ZO position of possible multiple reflections, prestack seismograms are calculated with the help of the corresponding CRS attributes. Here stacked amplitudes and wavelets are used for the generation of the seismograms. Then these seismograms are adaptively subtracted from the original data, to obtain multiple attenuated prestack data sets.

## THEORY

The basic idea of a this method for multiple attenuation is, predicting the multiples on the high quality CRS stacked sections, correcting these predictions, generating prestack multiple seismograms with CRS attributes, and afterwards adaptively subtracting these seismograms from the original input data. Important is, that the prediction of the multiples is not perfect, neither after the application of the correction term. It is an attempt that tries to maximize the fit between the prediction and the actual multiples on the stack.

First the basic ideas of multiple prediction by autoconvolution are revised, afterwards the correction term is discussed, and finally the adaptive subtraction with an additional step for reconstructing affected primary data is discussed.

### **Multiple prediction**

Multiple prediction by autoconvolution of stacked traces is based on the work of Verschuur et al. (1992) and the ideas presented in Kelamis and Verschuur (1996). Here the original Surface Related Multiple Elimination (SRME) process is simplified to the case that it can be applied to a single trace (i.e., 1d earth model) or stacked data, in our case CRS stacked data. In this approach the assumption is made that the stacked data can be considered as plane waves and a locally homogenous medium is assumed. This is not fulfilled in reality and results in prediction errors. For moderate inhomogeneous media this process can still predict multiples quite well. But nevertheless the prediction errors have to be addressed to get a better prediction of all multiples, this is done in the next section.

In contrast to the results presented last year, the approach was extended to all surface related multiples, by autoconvolving the whole stacked section by itself, so no picking is necessary. The basic idea is that an auto-convolution of a seismic trace x(t) with itself results in a first order surface related multiple prediction  $M_1(t)$  (after Verschuur (2006)):

$$M_1(t) = x(t) * x(t)$$
 (1)

Next the first order multiples can serve as a source for the second order multiples:

$$M_2(t) = M_1(t) * x(t) = x(t) * x(t) * x(t)$$
(2)

This can be repeated until n-th order. Since we are using the whole stacked section we have predictions of many surface related multiples at once. But due to the mentioned 1d approximations prediction errors for large traveltimes and steep dipping events are inherent. In the next section we will present an approach for correcting the biased predictions.

#### **Correction term**

In the search for a correction term for poststack multiple prediction we took a look at image processing algorithms. The problem is related to finding the best overlap between two images. Since we have a stacked section where we could especially enhance the multiples by allowing the stacking velocities to be significantly less than it would be for stacking primary reflections. We have the 'best' ZO position of the multiples and also the biased prediction from the ZO prediction process described above. Now the problem is how to find the best overlap between these two images, i.e., how to shift the prediction to match best the original stack. This can be done by a normalized 2d cross-correlation process. Since cross-correlation is a stationary process, it can only find a overall displacement for the whole section, which is not alway a suitable idea due to differential prediction errors. But the 2d cross-correlation algorithm can also be extended to the case of detecting subimages, which would lead to a windowed application of the correction term,

and therefore a differential correction.

Normalized cross correlation algorithms can be widely used for different applications where pattern matching is a key factor. Applications included time lapsed seismic data imaging (Hale, 2007), cell tracking in nano-biology (Perez-Careta et al., 2008), or fingerprint recognition (Karna et al., 2008).

To algin two 2d seismic images of the same size, one can use a normalized 2d cross correlation. The cross correlation of a stacked section and the multiple prediction can be written as

$$CC(\delta_x, \delta_t) = \sum_{x=0}^{ntr-1} \sum_{t=0}^{nt-1} STACK_{x,t} * PRED_{x+\delta_x,t+\delta_t}$$
(3)

where  $\delta_x, \delta_t$  denote the shift in space and time, respectively, *ntr* the number of traces, and *nt* the number of samples. *STACK* and *PRED* are normalized by the total number of samples in the data, e.g. *ntr* \* *nt*. When this formula is applied to two sections the correlation maximum gives an estimate of the total shift to best align these two sections. The shift is performed in lateral and time direction. Since this process is stationary, i.e., only an overall shift is determined, this simple process can only be applied in limited number of circumstances. More often this process will be applied in windowed way, which leads to the determination of subimages in a larger image, e.g. localizing a small portion of the prediction in the stacked section.

If the two seismic sections do not have the same size, additional steps have to be taken to localize the smaller portion of the multiple prediction. An intuitive way would be to pad the smaller seismic section with zeros. When applying this we encountered problems in the localization. The smaller prediction where placed in wrong positions. Investigation of this problem revealed that this happens mainly due to the mean values in the larger image. The cross correlation simplified calculates

$$CC = \sum \sum STACK_{x,t} * PRED_{x,t}$$
(4)

if the STACK has larger mean than the PRED this mean will be represented through out the whole cross correlation map. If the two section would have the same mean and variance from the mean, the localization would be successful.

So a modification of the cross correlation function is necessary. Assuming that  $x_1$  and  $t_1$  are the samples in the larger section,  $x_2$  and  $t_2$  are the samples in the smaller multiple prediction, and  $ntr_i$  and  $nt_i$  are the corresponding number of traces/samples, one can reformulate

$$CC(\delta_x, \delta_t) = \sum_{x_1=0}^{ntr_2 - 1} \sum_{t_1=0}^{nt_2 - 1} \frac{(STACK_{x_1 + \delta_x, t_1 + \delta_t} - \bar{A}) * (\dot{B} - \bar{B})}{\sigma_{A_{x_1 + \delta_x, t_1 + \delta_t}} * \sigma_{\dot{B}}}$$
(5)

where  $\dot{B}$  is the subimage at position  $\delta_x, \delta_t$ 

$$\dot{B} = B_{x_1 + \delta_x, t_1 + \delta_t}^{x_1 + nt_2 - 1, t_1 + nt_2 - 1} \tag{6}$$

This equation was modified in several places (compare to eq.(3)). First the summation is not over the entire stacked section. This is not very efficient, instead we can set all areas outside the smaller multiple prediction to zero, so that we can again sum over all samples. Second we have to subtract the mean of the stacked section and normalize it by the standart deviation. This requires additional preprocessing steps. When we combine these two steps we end up with a similar equation to the initial one.

The normalization of the stacked image can be achieved by a lowpass smoothing filter to construct the mean, subtract it from the stacked section, and afterwards normalize it by the standart deviation. The preprocessing of the portion of the predicted multiples is slightly more complicated, due to the lack of information outside the actual prediction. Because of this the calculation of the mean and standart deviation results in numerical errors. Therefore the length of the smoothing filter has to be adjusted to the smaller

image sizes. We have to enlarge the smoothing filter length to make it applicable to the prediction. Here we divided the number of samples of the prediction by two, to have significant contributions also at the edges of the smaller image, i.e. the multiple prediction.

After the correction of the multiple prediction in a windowed way, gaps in the predictions can occur, due to differential shifts of different portions of the multiple. To use the corrected prediction in the subsequent steps, we have to interpolate between the corrected subimages, this can be done according to Hale (2007) or with simple sinc interpolation if the corrected predictions are sufficiently close together.

#### Adaptive subtraction and data reconstruction

After this the corrected multiples can be used in the next processing step, the generation of prestack seismograms and adaptive subtraction.

Since we know the kinematic wavefield attributes of the multiples from the initial CRS stacking process and we have a fairly correct poststack multiple prediction. We can use this to generated multiple prestack seismograms. Since any adaptive subtraction process heavily relies on the result of the prediction, we include the stacked wavelet in the generation of the seismograms to get closer to the real solution. The multiples are generated in the second order hyperbolic approximation, and therefore the original data has to be muted to fit this approximation during the subtraction process.

For adaptively subtracting the multiples a simple Wiener Optimum filter (Yilmaz, 2001) is used. This adaptive filter is used at one CMP at a time in an application with moving windows in time and space to achieve maximum accuracy in the result. The filter parameters still have be chosen quite aggressively, due to the fact that still errors are present in the prediction. The 2d cross correlation process is a stationary process, i.e., only a total shift for the portion of the prediction can be found. Even in the windowed application of this approach, differential prediction errors are still present and can not be considered completely. The process is helpful, but still not a perfect correction. This sometimes results in filter artefacts in the data, where primary energy was also removed from the data.

With the help of the CRS prestack gather regularization (Baykulov and Gajewski, 2008) these filter artefacts can be significantly reduced. Initially this procedure was implemented to enhance low fold data and interpolate data gaps with the help of partial CRS stacks.

After the adaptive subtraction CRS stacking can be performed again. Most likely we are now able to stack up the primaries coherently. But small residuals from the multiples as well as filter artifact may occur in the data. But nevertheless quite reliable CRS parameters can be determined. These are afterwards used to recover the primaries in the data and reduce filter artifacts by partial CRS stacking. Basically the same geometry is considered as before. No traces are interpolated, but all traces are generated again by the partial CRS stacking process. This results in wavelets forms that more reflect the original shape before the agressive adaptive filtering process.

#### IMPLEMENTATION AND WORKFLOW

The multiple suppression loop of the expanded CRS-workflow is displayed in Figure 1. First a CRS stack is produced with special emphasize on stacking the multiple reflection coherently to obtain reliable CRS attributes for them. Therefore the stacking velocity intervals have to be significantly widened. Afterwards the multiples are predicted on the poststack section, by auto convolving each stacked trace with itself. This can be done in an automatic way without user interaction. Then the correction process is applied. Here the prediction is best matched to the stacked section where stacking was performed with special emphasize to stack up the multiples coherently. Depending on the prediction erros, the process is applied in a windowed way (subimage localization) or as a general shift (image comparison) for all multiples.

Now prestack seismograms of the multiples are generated. This is done by calculating traveltime curves in a hyperbolic sense, with the help of the CRS attributes and taking the stacked wavelet into account. To



**Figure 1:** Schematic illustration of the extra loop of the expanded CRS workflow, a new multiple prediction and correction element is added (red). Additionally the partial CRS stacking procedure for reducing filter artefacts is imaged (also in red).

constrain the subsequent adaptive subtraction process, only events exceeding a certain coherency threshold are generated. This avoids an application of the adaptive filter in regions with very weak multiples or multiples that can not be addressed by the hyperbolic assumption and helps to constrain the adaptive subtraction process to the main multiple contributions.

Afterwards the adaptive subtraction process is applied. Here every CMP is considered independently with moving windows in time and space. If necessary the filter parameters should be applied quite aggressively to account for small prediction errors still present in the data.

If the adaptive subtraction result also addressed primary energy unwontedly, the CRS prestack gather regularization by partial CRS stacks may also help. Here the CRS parameters and very small apertures can help to reconstruct affected data parts to their original quality. CRS attribues can be estimated after the first adaptive suppression, the resulting section might be affected by filter artifacts, but the attributes can still be obtained quite reliable. The partial CRS stack technique can make use of this and reconstruct the data without filter artifacts.

After successful application of this procedure, the CRS stack can be applied again on multiple attenuated data. Otherwise an additional application of this method can account for higher order multiples present in the data. The estimated CRS attributes can now be used for further applications, where only primaries are needed, e.g., NIP-wave tomography.

It should also be mentioned, that for a quick application of the described procedure the generation of a CMP stack is sufficient to apply this method. For this case the prestack seismograms are generated by using stacking velocities, but the CMP stack should produce sufficient coherent energy for all multiples to address.

# DATA EXAMPLE

The above described procedure to suppress multiples within the 'CRS-workflow' was applied to a data set from the Maldives. It was acquired in 2007 by the University of Hamburg and has a short streamer acquisition with maximum offsets of 700m and a CMP spacing 6.25m. The data was recorded up to two seconds TWT and covers a complex reef system between the islands of the Maldives. As can be seen on the stacked section in Figure 2 between 0.8s and 1.2s a band of multiple reflections covers primary reflections.



**Figure 2:** Stacked section of the Maldives data set. Multiple reflections occur as whole bands and cover primaries mainly in the areas between 0.8s and 1.2s.

After the prediction was generated by the poststack autoconvolution, the prediction was corrected by a global shift based on the result of the image comparison algorithm. The whole prediction was shifted 2 traces to the left and 13 samples down. The resulting cross correlation values are displayed in Figure 3. The difference from the maximum of the function and the middle of the section determines the shift to apply.

Although the overall shift seems to work quite well in this case, the windowed application is also presented. Therefore we cut a small portion of the multiple prediction of 500 traces and 500 samples and try to find the correct position on the stack (subimage processing). The zero padded portion (To the portion of the prediction zeros are added to have the same section size as the stack) serves as input (image position 0,0) to the algorithm. This subimage can be found on the stack at the correct position as can be observed in Figure 4. The estimated shift is 999 traces and 1013 samples.

With the improved multiple prediction we can generate prestack seismograms using the CRS attributes of the previously stacked multiples. The wavelets and amplitudes of the stacked sections are taken into account. To start the adaptive subtraction process the original input data has to be muted according to the hyperbolic approximation. The result of the adaptive subtraction is CRS stacked again and a multiple attenuated stack is obtained. The stacking result can be seen in Figure 5. Esspecially in areas around CMP 1400 many previously covered primary reflection became visible. But the data also seems to be affected by the quite aggressive application of the adaptive subtraction.

An optional step in areas of heavily affected primaries is to use the data reconstruction ability of the partial CRS stack. In the areas around CMP 1400 one can see slight filter artefacts, where multiple removal also affected primary reflections. This is a problem, especially for short streamer acquisition, where primaries



**Figure 3:** 2d cross correlation values. The maximum of the cross correlation function estimates a shift of 2 traces to the left and 13 samples in the positive time direction.

and multiples have almost the same moveout. In Figure 6 the stack result of the reconstructed data is imaged in comparison with the affected data. The filter artifacts were successfully removed after partial CRS stacking with small apertures to ensure no unnecessary data interpolation.

# CONCLUSIONS AND OUTLOOK

We have presented a continued development of an approach for multiple attenuation within the CRS workflow. It assumes hyperbolic moveout of the multiples. The algorithm relies on the principles of predicting the multiples in the poststack data domain and subtracting them in the prestack data domain. The predicted multiples are transformed to the prestack data domain by the CRS attributes, estimated for the multiples.

The approach was extended to be independent from user interaction (picking of main multiple generating horizons) and a correction term is introduced based on 2d cross correlation algorithms. The correction term is not valid for all estimated multiples, but can produce sufficient results to address the main prediction errors. Alternatively a global shift or a windowed application of the correction term is possible.

The results of the Maldives data set show the potential of the extended method, where a lot of multiples energy could be removed and primary energy recovered. But it also has to be mentioned that this is a rough prediction error estimation for an overall correction, it is not as accurate as a 2d SRME prediction for example. But it can still produce reasonable results, as can be seen on the data example. Also the algorithm is restricted the the hyperbolic assumption, i.e., in complex geologic situations this assumption may be violated and the algorithm fails.

The main advantage of this approach is its simplicity and speed. The algorithm is also independent of data regularization and can handle sparse data. As long as reliable CRS attributes can be determined and the prediction is quite accurate, surface related multiples can be attenuated without data regularization. Also insufficient velocity discrimination is not a big issue since the CRS stack can be quite good constrained to



**Figure 4:** The original stacked section with multiples (in gray scale) overlaid by the estimated windowed shift of the portion of the predicted multiples (in red and blue).

detect multiple parameters reliable. Also aggressive application of the adaptive subtraction can be removed by applying local CRS stacks to the data to reconstruct the affected primaries.

The further extension of the method may comprise to include CRS gathers into the adaptive subtraction process. According to (Verschuur, 2006) this may lead to balancing of the prediction errors in the sub-traction process, since in a CRS gather many CMP gathers are included and small timing errors may be balanced. Also the more accurate prediction of the multiple amplitudes by CRS attributes is an interesting research topic. It also can be thought of extending the prediction to the 2d case, by performing the 2d SRME process with CRS regularized gathers. This would lead to better predictions and could reduce the dependence on the adaptive subtraction process.



**Figure 5:** CRS stacked section of the profile after multiple suppression. As can be seen lot of multiple energy could be removed from the stack.

# ACKNOWLEDGMENTS

This work was kindly supported by the sponsors of the *Wave Inversion Technology (WIT) Consortium* and by the fundings of the German Research Council DFG/IODP (Project number HU698/14-1). The Maldive data set was kindly provided by Dr. Thomas Lüdmann. Parts of the codes were used from the 'yellowcouch.org' project.

#### REFERENCES

- Baykulov, M. and Gajewski, D. (2008). Seismic data enhancement with partial common reflection surface stack. *submitted to Geophysics*.
- Dümmong, S. and Gajewski, D. (2007). A multiple suppression method via crs attributes. *Wave Inversion Technology report*, pages 82–93.
- Duveneck, E. and Hubral, P. (2002). Tomographic velocity model inversion using kinematic wave-field attributes. *SEG Technical Program Expanded Abstracts*, pages 862–865.
- Gamboa, F., Filpo, E., and Tygel, M. (2003). Multiple attenuation using common-reflection-surface attributes. *Wave Inversion Technology Annual report 2003*, pages 92–100.
- Hale, D. (2007). A method for estimating apparent displacement vectors from time-lapse seismic image. *SEG Expanded Abstracts 26*.
- Hertweck, T., Mann, J., Duveneck, E., and Jäger, C. (2003). Crs-stack-based imaging workflow theory and synthetic data example. *Wave Inversion Technology Annual report 2003*, pages 140–149.



(a) Affected data

(b) Recovered data

**Figure 6:** Comparison between the CRS stacking result of the multiple attenuated data set (a) and the same data set where filter artefacts were reduced by the partial CRS stacking process (b). Especially between 1.0s and 1.2s filter artefacts could be removed.

- Karna, D., Agarwal, S., and Nikam, S. (2008). Normalized cross-correlation based fingerprint matching. *Computer Graphics, Imaging and Visualisation modern techniques and applications, proceedings.*
- Kelamis, P. and Verschuur, D. (1996). Multiple elimination strategies for land data. 58th Meeting, EAGE, *Expanded abstracts*, page B001.
- Mann, J. (2002). *Extensions and Applications of the Common-Reflection-Surface Stack Method*. Ph. D. thesis, University of Karlsruhe.
- Perez-Careta, E., Torres-Cisneros, M., Avina-Cervantes, J., Debeir, O., Ibarra-Manzano, O., Aguilera-Gomez, E., Perez-Pantoja, E., and Negrete-Romero, G. (2008). Cell recognition and tracking using nonlinear cross-correlation. *Digest of the Leos summer topical meetings*.
- Ryo, J. (1982). Decomposition (decom) approach applied to wave-field analysis with seismic reflection records. *Geophysics*, pages 869–883.
- Verschuur, D. (2006). Seismic multiple removal techniques. EAGE Publications.
- Verschuur, D., Berkhout, A., and Wapenaar, C. (1992). Adaptive surface-related multiple elimination. *Geophysics*, pages 1166–1177.
- Wegelein, A., Gasparotto, F., Carvalho, P., and Stolt, R. (1997). An inverse-scattering series method for attenuating multiple reflections in seismic data. *Geophysics*, pages 1975–1989.

Yilmaz, O. (2001). Seismic data analyses. Society of Exploration Geophysicists, Tulsa.