

# Deep water OBN multiple prediction from local reflectivity in Stolt Domain

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## Introduction

In deep water Ocean Bottom Node (OBN) surveys, the use of downgoing data post-wavefield separation is a common practice due to its illumination capabilities facilitated by mirror migration. As the depth of the survey increases, so does the discrepancy in illumination between the upgoing and downgoing wavefields. Irrespective of the employed wavefield separation method, the downgoing wavefield consistently harbors a more pronounced presence of free surface multiples compared to the upgoing wavefield, necessitating the application of multiple attenuation techniques.

Many techniques exist for mitigating multiples in OBN surveys. Among these methods are convolutional techniques such as Model-based Water-layer Demultiple (MWD, Wang et al. 2011) and Surface Related Multiple Elimination (SRME - Verschuur et al, 1992). While adept at predicting complex multiples, these techniques mandate supplementary data not readily available within the node itself. MWD, for instance, is confined to predicting water-bottom related multiples and hinges on precise bathymetry data. Conversely, SRME requires additional data from towed streamer acquisition due to the complexities associated with redatuming from the water bottom to the free surface. Despite this, sourcing existing towed streamer data from the same area as the OBN survey is usually not an issue. SRME predictions exhibit limited bandwidth due to the convolutional process's squaring of the wavelet, however, all free surface multiples are predicted. Given their complementary attributes, MWD and SRME are often both employed to predict multiples in deep water OBN surveys, followed by simultaneous least squares adaptive subtraction.

Another category of techniques, known as deconvolutional methods, exclusively leverages data within the node itself to predict multiples, commonly in the Frequency-Kx-Ky (FKK) or Tau-Px-Py domains. One of the better known techniques that has been used for years in the industry is  $\tau$ - $p$  deconvolutions, feasible for 3D implementation in OBN datasets due to the available shot sampling for each node.  $\tau$ - $p_x$ - $p_y$  deconvolution operates on the premise of transforming  $x$ - $t$  domain data into a domain where diverse dips, corresponding to different plane waves, are mapped to distinct regions where multiple periodicity is better organized. Predictive deconvolution then assumes that true reflectivity is random and any periodicity manifests as organized energy in the autocorrelation, subject to attenuation depending on its location relative to the zero-lag. This restriction distance, often termed the "gap", correlates

well with the seabed's depth, with larger gap values ensuring a safer process given the non-random nature of the Earth's reflectivity.

## Theory

The Stolt domain, here referred to as the forward 3D time-migrated image utilizing constant water velocity, constitutes a lossless transformation for all events surpassing water velocity. It is computationally efficient because it uses simple operators in the  $f$ - $k_x$ - $k_y$  domain. Predominantly, it collapses most primary and multiple energy to near zero offset. For a flat Water Bottom (WB), the free surface WB-related multiples can be accurately predicted by simply offsetting the data by twice the WB travel time at zero offset. However, deviations from a flat WB and the existence of non-WB free surface multiples complicate the kinematic relationship primary-multiple. We propose computing a three-dimensional operator  $F(x', y', t')$  in the Stolt domain to minimize the following cost function:

$$J = \|D(x', y', t') - F(x', y', t') * D(x', y', t' - 2 * \text{rec\_z} / w_{\text{vel}})\|^2 \quad (1)$$

with receiver depth  $\text{rec\_z}$  and water velocity  $w_{\text{vel}}$ , where  $D(x', y', t')$  = Stolt[ $D(x, y, t)$ ] is the input data in the Stolt domain and  $F(x', y', z')$  is .... An initial estimate of  $F(x', y', t')$  can greatly help the convergence of this process and it is derived from a local estimate of primary reflectivity. Then the multiple prediction  $M$  becomes:

$$M(x, y, t) = \text{Stolt}^{-1}[F(x', y', t') * D(x', y', t' - 2 * \text{rec\_z} / w_{\text{vel}})] \quad (2)$$

This multiple model is then directly subtracted in the  $(x, y, t)$  domain or could be adapted using traditional L2 energy minimization techniques, thus avoiding issues of having FKK to the data ?

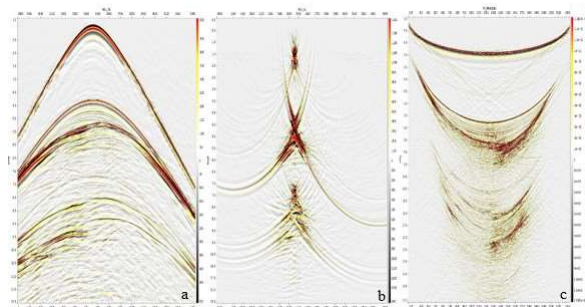


Figure 1: (a)XT, (b)Stolt and (c)TauP domains

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Figure 1 provides a comparative analysis across three distinct domains:  $x-y-t$ , Stolt, and TauPxPy. Analogous to the XT domain, the TauPxPy domain exhibits a convergence of multiples with corresponding primaries in far offsets. In essence, this convergence translates to a diminishing window between primaries and multiples as the offset increases. Within the realm of predictive deconvolution, this phenomenon necessitates the use of smaller gaps to forecast far offset multiples, thereby rendering deconvolution riskier at these offsets.

Conversely, within the Stolt domain, a distinct pattern emerges. Here, primary and multiple events appear to collapse near zero offset with somewhat consistent separation between primaries and multiples. This eliminates the need for smaller gaps to predict far offset multiples. However, the amalgamation of near and far offset energy in this domain introduces complication, increasing the complexity of the operator needed to accurately predict the multiples. We rely on the inversion process delineated in equation (1) to produce the required filter for an accurate multiple prediction. The inherent separation between primary and multiple events within the Stolt domain serves as a mitigating factor, rendering the deconvolution process comparatively safe for the primaries.

### Example

We conducted an evaluation of the proposed methodology utilizing a dataset from a deep water Ocean Bottom Node (OBN) survey in Brazil. We performed wavefield separation below the seabed through adaptive PZ summation in the 3D curvelet domain, yielding the required downgoing wavefield dataset. This approach, characterized by its ability to simultaneously perform obliquity correction, shear wave denoise, local calibration, and wavefield separation, streamlining the data processing into a single efficient step. However, the resultant downgoing wavefield exhibits the presence of both receiver side ghost and free surface multiples. While mirror migration facilitates the utilization of the first WB multiple for enhanced shallow illumination during imaging, it is necessary to address the higher-order free surface multiples.

To illustrate the impact of the deconvolution filter outlined in equations (1) and (2), we initially show the resultant multiple prediction by setting the filter to a value of 1. This configuration corresponds to a prediction exclusively accounting for WB related multiples. However, such a prediction proves inherently inaccurate due to the implicit assumption of a flat WB, evidenced by discrepancies arising from variations in the WB reflector dip, particularly evident at far offsets. To facilitate a comprehensive comparison, we present both the input data and multiple predictions across

the XT and Stolt domains, juxtaposed with predictions generated using the MWD technique for reference. MWD, a method adept at incorporating WB variations observed at each receiver, employs this information to calculate time delays in neighboring traces, thus enhancing the accuracy of its predictions. With the MWD method relying on precise bathymetry data.

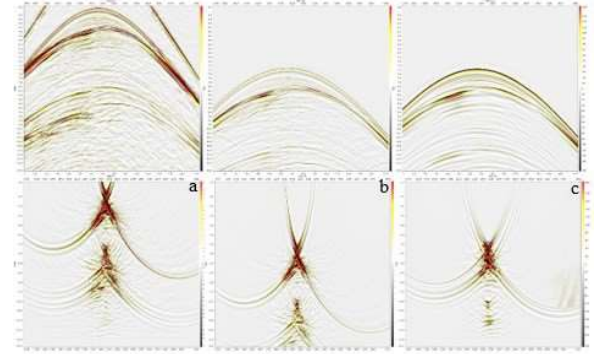


Figure 2: (a)input, (b)shifted input and (c)MWD model. XT domain at top, Stolt at bottom

Subsequently, we refine our multidimensional filter to match the shifted version of the input to the multiple, resulting in a significantly improved model for both the Stolt and XT domains in the full bandwidth. We compare this result with the 3D SRME accurately predicts all free surface, contingent upon the availability of the auxiliary towed streamer dataset. The accuracy of the SRME model is primarily data-driven, leveraging auxiliary data to compensate for its inherently limited bandwidth arising from the convolution of two band-limited signals. Its superiority can be noted in predicting complex multiples necessitating a broad aperture for prediction, underscoring the advantages afforded by the utilization of auxiliary data to refine these predictions. In contrast, Stolt deconvolution, akin to its deconvolution counterparts, draws solely from the node being processed, thereby constraining its capacity to model intricate multiple features. The multidimensional filter derived from the optimization process accommodates kinematic adjustments in far offsets, while incorporating reflectivity information crucial for predicting non-WB multiples. The multidimensional shift operator can be understood as the reflectivity, where a flat WB manifests as a layer of single time delay spikes. Figure 3 compares input, Stolt deconvolution and SRME models in XT and Stolt domains. Figure 4 shows pre-stack depth migration stack comparisons before and after Stolt deconvolution, and the noise removed.

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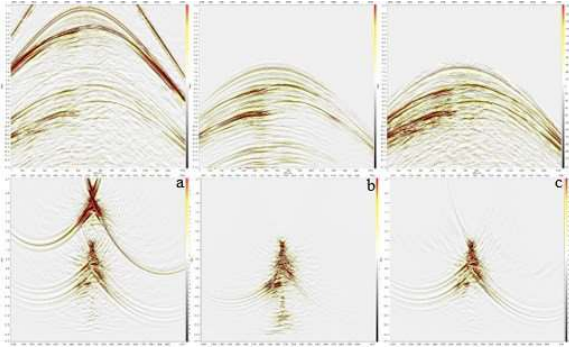


Figure 3: (a)input, (b)SRME model, (c)Stolt deconvolution model. XT domain at top, Stolt at bottom

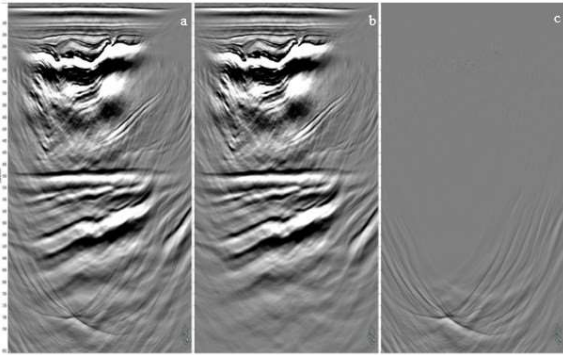


Figure 4: (a)Input PSDM stack, (b)PSDM stack after Stolt deconvolution model, (c) Difference

### Conclusions

In the context of deep water environments characterized by substantial separation between primary reflections and multiples, Stolt deconvolution emerges as a swift and efficient technique for mitigating multiples from Ocean Bottom Node (OBN) downgoing wavefields. Leveraging shot carpet sampling, this three-dimensional data domain facilitates enhanced focus and segregation between multiples and primaries, thereby augmenting the safety and efficacy of the deconvolution process, with respect to primary reflections.

Notably, the predictive capability of this method encompasses the full bandwidth spectrum, rendering it adept at accurately forecasting all free surface multiples. This proficiency is attributed to the intricate nature of the inverted filter, which navigates the complexities inherent in the seismic data to yield precise predictions across the entire frequency range.