Deblending of long-offset OBN data for velocity model building by sparse inversion of hyperboloidal components

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Summary

We studied the feasibility of deblending of ocean bottom node (OBN) data with the purpose of using low frequency long offset signals for full waveform inversion (FWI) velocity-model building. We used unblended field records to simulate heavily blended data up to 8 Hz with a maximum offset of 30 km. Our inversion-based deblending method involves many iterations of separating the most coherent hyperboloidal events in a cube of data formed by all traces recorded in a single node. Coherent hyperboloidal components are modeled by using an amplitude threshold in the 3D *f-k* domain, while various temporal shifts are applied. The leakage of blending noise into the estimated model is then reduced by using further coherency enhancement algorithms during the inversion process. This study shows that it is possible to reveal the signals required for an FWI workflow.

Introduction

Acquiring seismic data in a 'blended' style has become a new standard, and several deblending methods have been developed for various scenarios. A common way of acquiring blended data is continuously recording while multiple sources are firing impatiently, causing interference in their wavefields. This approach not only reduces the acquisition cost, but also facilitates an increase in the trace density in all directions. A continuous record is then fragmented into conventional truncated records. Hence, each desired record is contaminated with weak noise from preceding shots, and strong noise from next shots. Once the records are arranged based on their intended zero times, desired signals appear coherent, and blended data appear incoherent in both inline and crossline directions.

Abma et. al. (2010) proposed a method of separating the overlapping wavefields by using sparse inversion. Zhan et. al. (2015) presented a data-driven deblending scheme which uses a combination of adaptive subtraction and median filtering to separate simultaneous sources recorded in OBN data. Masoomzadeh et. al. (2018) presented an inversion-based method applicable to streamer data, that estimates the deblended model by capturing and accumulating hyperbolic cylindrical components via horizon flattening and various constant moveout corrections in different iterations. In this paper we extend the latter method to the field of OBN data.

The aim of this study is to find an answer for the following question: if we plan to acquire blended long-offset OBN data, using 3 source vessels towing a pair of air gun arrays each, and sailing 10 km apart, is it possible to successfully reveal the low-frequency refractions required for an FWI study? To answer this question, we used an unblended OBN data set to simulate the above scenario, then we used the method presented here to deblend that data set.

Deblending OBN data with sparse inversion

Our inversion-based deblending method, involves iterations of modeling the most energetic and coherent events, updating and enhancing the total model, reblending the latest model and subtracting the result from the input data to work out the residuals, until the residual energy is insignificant. This process is performed in a cube of data containing successive inline gathers transformed into the frequency domain. Every frequency slice is then transformed into the *kx-ky* domain, where amplitudes are calculated and normalized. While in the transformed domain, we apply a criterion so that only those elements with a higher amplitude than a given threshold will be accepted and inverse transformed. This thresholding criterion passes sparse components corresponding to hyperboloids in the time-space domain.

Since the coherent energy in the node data is mainly from hyperboloidal events, we apply constant moveout shifts before performing the spatial transformation and reverse the shifts after the inverse transformation. This feature not only supports modeling more coherent energy in a smaller number of iterations, but also enhances the antialiasing feature of the method. These shifts are expected to flatten 3D surfaces corresponding to strong events in the data, such as the direct arrival event and its multiples. As a result of this, hyperboloidal events become more likely to participate in the formation of the deblended model than other events. To give a fair chance to those events that do not fit into a hyperboloidal pattern, we apply the temporal shifts for four iterations, corresponding to the two-way-times of the seabed event and its first to third multiples, then we turn this shifting feature off for another four iterations. In the next round of shifting we use a different velocity in the hyperboloid equation, to address a new set of events.

Finally, since some blending noise can leak into the model domain, we apply more constraints to the model. For example, we apply a tapered mute above the direct arrival times, and an *f-x* deconvolution operation in the inline direction to reduce the leaked random noise. Since the node data is essentially a receiver gather, we apply a velocity filter while in the *kx-ky* domain. Furthermore, a time-frequency trimming process can be applied to overlapping trace

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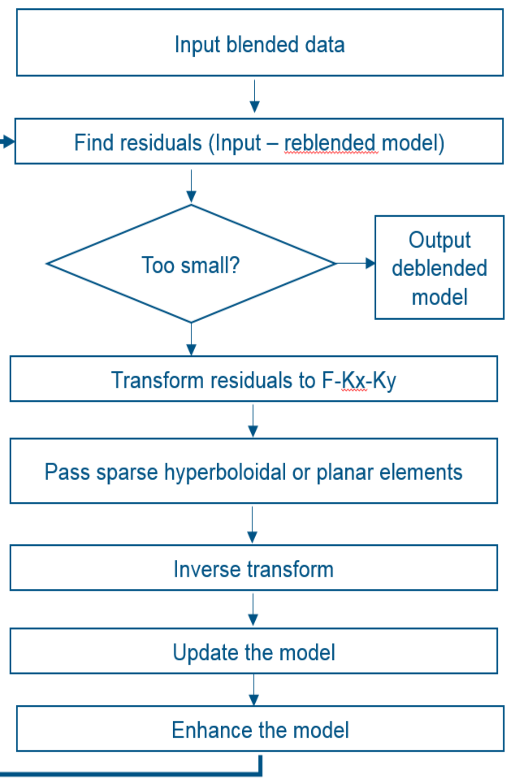

Figure 1: A schematic expression of the inversion algorithm used for OBN data deblending.

segments. The frequency content of a noisy segment is adjusted based on a comparison against the median amplitude of its adjacent traces. Obviously, the rejected elements will be given a new chance to reappear in a more coherent form in the next iterations. A summary of the procedure explained above is presented by a flowchart in Figure 1.

Test data

Aiming to evaluate practical challenges of deblending OBN data acquired using 3 source vessels firing independently, we first decided to synthesize the intended acquisition scenario by using a legacy OBN dataset. The original dataset was acquired using one source vessel sailing at a speed of 4.5 knots firing every 25 m, with 100 m crossline intervals. Since the aim of this study is to focus on low frequencies and long offsets, we rearranged the recorded data into 40 s trace length, applied a high-cut filter at about 8 Hz and increased the sample rate to 50 ms.

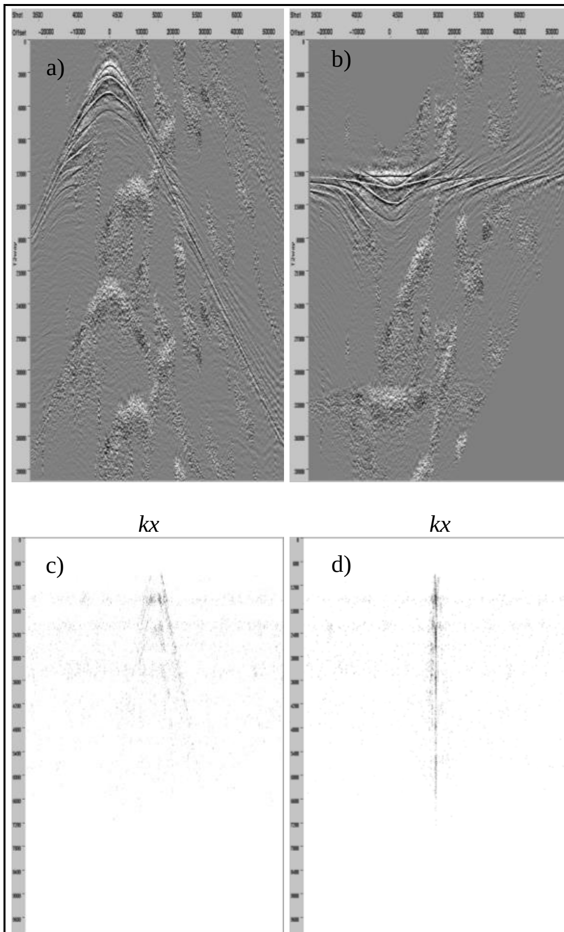

Figure 2: a) An inline gather from a blended OBN data set, b) same gather after the application of hyperboloidal shifts. c) energetic components in the *f-k* domain before flattening, d) energetic components after flattening. It can be seen that while random features remain as random, coherent events are more focused around the center. This in turn improves the chance of segregation of desired coherent components from undesired incoherent noise by using an amplitude threshold.

Figure 2 shows one of the inline gathers of the synthetically blended data, both before and after the application of constant moveout shifts. This figure shows that event flattening helps further concentration of coherent energy around the central *k* component, which in turn improves the chance of separation of coherent events from the incoherent random features in the background based on their amplitude levels in the transformed domain.

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Figure 3 shows an inline gather of the original unblended data, both before and after blending it with the data received from other shots in the same node, and after deblending using the method explained in the previous section of this paper.

Not dissimilar to many other inversion schemes used in the field of seismic data analysis, the scheme presented above is also prone to the non-uniqueness problem. Hence, during the inversion process we impose further constraints to the latest solution to help it move further towards the ideal solution or the global minimum.

Firstly, we apply a tapered top mute to the estimated model of deblended data. This muting is applied above the time at which the earliest arrivals, i.e. direct arrivals and refractions, are expected to be present. Secondly, since the node data is a 3D common receiver gather, no signal is expected to appear with a ray parameter larger than that of direct arrivals. Hence, while the data is in the transformed domain, we apply a velocity filter to suppress any components appearing outside the data cone. Finally, in every 5th iteration we apply an *f-x* deconvolution in the inline direction to remove the random features that may have leaked into the model domain. Figure 4 demonstrates the effect of velocity filtering and *f-x* deconvolution on the result of inversion both in the *t-x* and in the *f-k* domains

It is worth mentioning that the rejected noise will appear as part of the inversion residuals in the next iteration, therefore it will be given a new chance to reappear in a more coherent form. Hence, implementing the above criteria can be considered as a coherency promotion strategy.

Conclusions

Aiming to examine practical aspects of long offset OBN data deblending we used an existing unblended data set to generate blended data and then deblend it, using our inversion-based algorithm. We iteratively model the most strong and coherent hyperboloidal events including direct arrivals by applying time shits after transformation to the frequency domain, and before transformation to the *kx-ky* domain. Aiming to suppress the residual interfering noise, we apply various filters and constraints to the latest estimation of the deblended data, which shows to help improve the result.

Acknowledgements

The authors would like to thank Shell for granting permission to show the OBN data set used in this study. Also, we are thankful to Connie VanSchuyver for proofreading this paper.

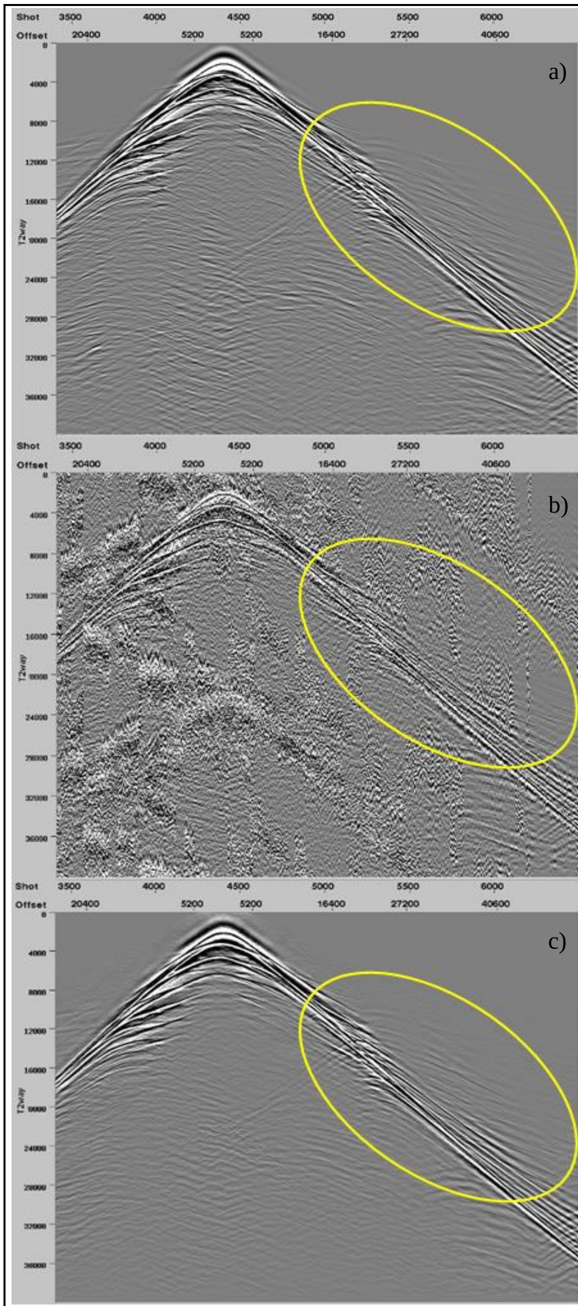

Figure 3: a) An inline gather acquired without any blending interference; b) the same gather when an intended blending scenario is synthesized; c) after deblending the latter by using our sparse inversion method aiming to model the most coherent hyperboloidal and planar components. Zone of interest for FWI study is highlighted by ellipses. It can be seen that a reasonable level of recovery is achivable in the low frequency and long offset range.

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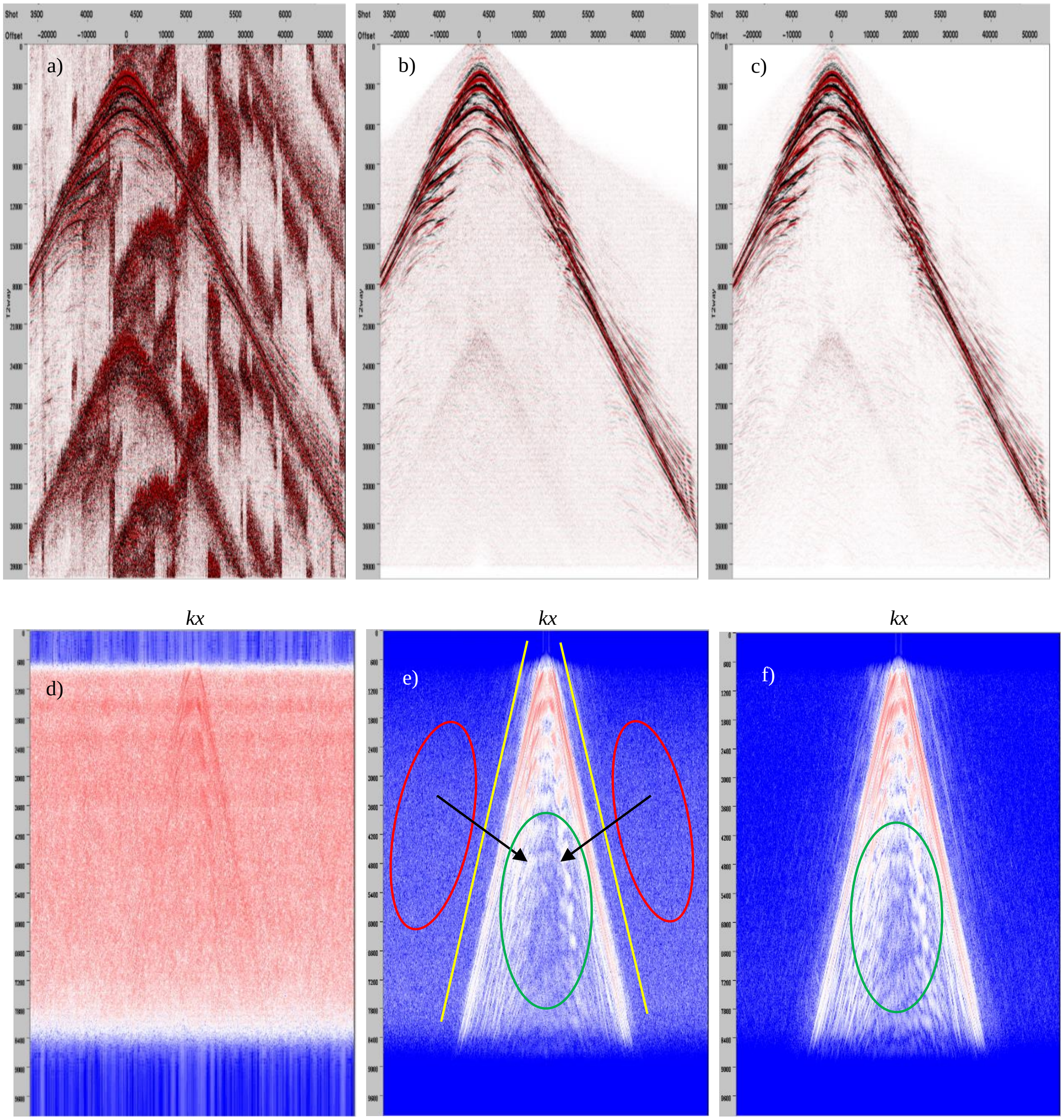

Figure 4: A demonstration of the improvement that can be achieved by imposing further coherency promotion tools. a) an inline gather before deblending, b) after deblending while a top mute of the model is applied during the inversion process, c) after deblending while both velocity filtering and random noise attenuation by usning an *f-x* deconvolution tool are in place. d) to f) Logarithmic amplitude spectra of a) to c) in the *f-kx* domain. It can be seen that the remaining backgroun noise is larger in the higher frequencies. That is because higher frequencies are less likely to appear coherent. This noise is reduced noticably by the application of further criteria. Since the rejected noise are given a chance to reappear as more coherent signals, the weaker events in the deblended model, highlighted by green ellipses, appear to become stronger.

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