Iterative separation of blended marine data: discussion on the coherence-pass filter

Panagiotis Doulgeris, Araz Mahdad, and Gerrit Blacquière, Delft University of Technology*

SUMMARY

In conventional marine acquisition surveys the time intervals between the firing of successive sources are large enough to avoid interference in time. To obtain an efficient survey, the spatial source sampling is therefore often (too) large. However, much attention has been drawn recently to blended acquisition designs, where sources are shot in an overlapping fashion. Waiving the constraint of no overlap can potentially lead to significantly improved quality or economics since more sources can be utilized in a given time frame.
Deblending is the procedure of recovering data as if they were acquired in the conventional, unblended way. A simple least-squares procedure however, does not remove the interference due to other sources, or blending noise. Fortunately, the character of this noise is different in different domains, e.g., it is coherent in the common source domain, but incoherent in the common receiver domain. Hence, a proper coherence-pass filter should be able to discriminate between signal and blending noise. Furthermore, such a filter can be integrated into a regularized inversion scheme, where the separation is performed in an iterative way. Three types of such coherence-pass filters, $f-k$, $f-k_r-k_s$, and $\tau-p$, are presented here as part of a steepest-descent type of algorithm. When applied to a numerically blended field dataset, the $\tau-p$ filter outperforms the other two.

INTRODUCTION

Methods to utilize more than one source simultaneously in the field are common practice in land surveys, see Bagaini (2006). In these methods, the resulting records do not suffer from interference in space or time. A change in mindset though is occurring the last few years with land surveys that do not obey the constraint of no overlap, see Howe et al. (2009) and Pecholcs et al. (2010). Such a paradigm of productivity increase has not been realized for the marine case yet. The use of simultaneous sources in marine surveys was introduced by Beasley et al. (1998). This notion was extended to incoherent shooting and blending by Berkhout (2008) in order to achieve better illumination of the subsurface, see also Berkhout et al. (2010). The blended data acquired by such a survey contain interference or blending noise and can either be processed by specially designed least-squares migration algorithms, see Dai et al. (2010), or be first separated and then further processed with conventional tools. In the current paper we focus on the latter.

The separation process (deblending) for the marine case can be regarded as a denoising problem, treating the interference due to blending as noise. It has been reported by various authors - e.g., Moore et al. (2008), Akerberg et al. (2008) - that by sorting the acquired blended data into a different domain than the common source domain, e.g., the common offset domain, the blending noise appears as random spikes; thus, the separation process turns into a typical random noise removal procedure. Based on this property, Huo et al. (2009) use a vector median filter after resorting the data into common mid-point gathers. Kim et al. (2009) build a noise model from the data itself and then adaptively subtract the modeled noise from the acquired data. This algorithm is implemented in the common offset domain.

Deblending can also be formulated as an inversion problem that estimates the unknown unblended data. Since this is an ill-posed problem, a regularization term is required. Moore (2010) uses a sparsity constraint in the radon domain in order to regularize his inversion. A sparsity constraint is also utilized by Abma et al. (2010) in order to minimize the energy of the incoherent events present in the blended data. An inversion approach that is also based on coherence in some domain was proposed by Mahdad and Blacquière (2010) and Doulgeris et al. (2010b). This work was later extended to a general framework that could integrate any multi-dimensional coherence-pass filter, see Doulgeris et al. (2010a). In the present work, three types of such coherence-pass filters are used inside this inversion scheme and their results are evaluated.

METHOD

The matrix notation

Berkhout (1982) showed that seismic data can be arranged in the so-called data matrix $\mathbf{P}$. Each element P_{kl} is one temporal frequency coefficient of the trace that contains the response of the source array l as recorded by the detector array k. Hence, a column of the matrix $\mathbf{P}$ describes a shot record, whereas a row describes a common detector gather. In this context, blending can be very easily written as a multiplication of the data matrix with a blending matrix $\mathbf{\Gamma}$:

$$\mathbf{P}' = \mathbf{P}\mathbf{\Gamma}. \quad (1)$$

The $\mathbf{\Gamma}$ matrix describes how blending was performed in the field and its elements are phase and/or amplitude terms. Each column $\mathbf{\Gamma}_l$ is related to one blended shot record and its elements Γ_{kl} are the source codes that can be phase and/or amplitude terms. For example, in the simple case of a marine survey with random firing times, $\Gamma_{kl} = e^{-j\omega\tau_{kl}}$ expresses the time delay τ_{kl} given to source k in blended source array l.

Iterative Deblending

In order to restore the *unblended* data from the measured data, an inversion process has to be carried out on equation 1. A first approach is to compute the pseudoinverse of $\mathbf{\Gamma}$. It can be shown that in the case of phase encoding this is a scaled version of the complex conjugate transpose:

$$\langle \mathbf{P} \rangle = \mathbf{P}'\mathbf{\Gamma}^H \quad (2)$$

where $\langle \mathbf{P} \rangle$ is the so-called *pseudodeblended* data matrix and the superscript H denotes the complex conjugate transpose.

From the physics point of view, this process corrects for the time delays introduced in the field. However, it does not separate the responses from the different sources resulting in contamination of the pseudodeblended result with blending noise. Such a separation process will now be discussed.

Since the operation of blending is exactly known -in terms of time delays- the interference introduced to the pseudodeblended data could be computed exactly if the unblended data $\mathbf{P}$ were known. However, the initial unblended data are not available and obviously, if they were there would be no need of such a deblending method. Suppose though, that *part* of $\mathbf{P}$ could be extracted from the pseudodeblended data $\langle\mathbf{P}\rangle$. Then, an iterative estimation - subtraction process could be initiated where more of the blending noise could be removed at each iteration. Such a method is depicted in figure 1 and can be mathematically formulated using the matrix notation:

$$\mathbf{P}^{i+1} = \mathbf{P}'\mathbf{\Gamma}^{H} - \overline{\mathbf{P}^{i}}(\mathbf{\Gamma}\mathbf{\Gamma}^{H} - \mathbf{I}), \tag{3}$$

where $\mathbf{P}^{i+1}$ is the deblended estimate on iteration $i+1$ and $\overline{\mathbf{P}^{i}}$ is the deblended estimate on iteration i processed in such a way that only *unblended* data are contained. The second term on the right hand side of equation 3 transforms the estimated unblended data $\overline{\mathbf{P}^{i}}$ into blending noise. This is achieved by blending and pseudodeblending $\overline{\mathbf{P}^{i}}$ by applying the term $\mathbf{\Gamma}\mathbf{\Gamma}^{H}$ while making sure that the initial signal is removed by subtracting $\overline{\mathbf{P}^{i}}\mathbf{I}$. This noise estimate can then be subtracted from the pseudodeblended data, providing a better estimate of the unblended data for the new iteration. Repeating this process leads to the gradual removal of blending noise from the pseudodeblended data, until no further improvement is achieved.

It is interesting to notice the resemblance of equation 3 with the steepest descent method. A steepest descent iteration in matrix notation would be

$$\mathbf{P}^{i+1} = \mathbf{P}^{i} + \alpha^{i+1}(\mathbf{P}' - \mathbf{P}^{i}\mathbf{\Gamma})\mathbf{\Gamma}^{H}, \tag{4}$$

with $\mathbf{P}^{0} = 0$ and α being the step length. In the absence of noise in the forward model, i.e., when the blending parameters are known precisely, the blending matrix $\mathbf{\Gamma}$ can be chosen such that the diagonal of the $\mathbf{\Gamma}\mathbf{\Gamma}^{H}$ matrix is populated with ones. In this case, the parameter α should be equal to 1. Equation 4 can then be written as

$$\mathbf{P}^{i+1} = \mathbf{P}'\mathbf{\Gamma}^{H} - \mathbf{P}^{i}(\mathbf{\Gamma}\mathbf{\Gamma}^{H} - \mathbf{I}). \tag{5}$$

In order to regularize this inversion an extra constraint is introduced that will lead the inversion to the most coherent solution. For this reason, a projection of the current estimate onto the feasible set is required, i.e., the set of coherent signals in the model space. This projection can be implemented as a coherence-pass filter. If we denote the projected $\mathbf{P}^{i}$ as $\overline{\mathbf{P}^{i}}$, then equation 3 is obtained.

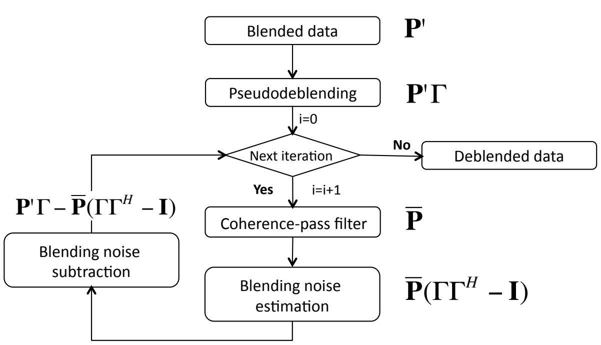

Figure 1: The flowchart of the deblending algorithm.

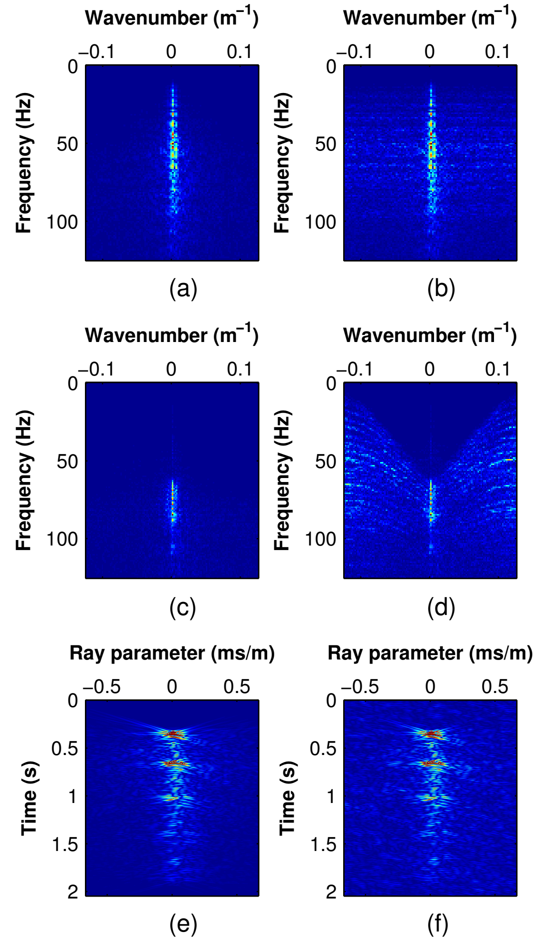

Figure 2: (a)-(b) $f-k$ spectra of an unblended and a pseudodeblended common offset gather respectively, (c)-(d), the $k_s = 0$ slice of the $f-k_r-k_s$ spectra of an unblended and a pseudodeblended dataset respectively, and (e)-(f), an unblended and a pseudodeblended common offset gather in the $\tau-p$ domain respectively.

Coherence-pass filters

The estimate of the unblended data $\overline{\mathbf{P}^{i}}$ can be obtained by a processing step. Any kind of process capable of distinguishing between coherent and incoherent events can be integrated in this step. Three implementations of a coherence filter are studied in this paper. All of them consist of a filter in some domain followed by a thresholding process.

$f-k$ filter

The blending noise present in pseudodeblended data is not continuous in the lateral sense when the data are sorted in common detector, common offset or common mid-point gathers. Hence, transforming such a gather in the $f-k$ domain, i.e., perform a 2D Fourier transform, reveals that the blending noise has a white spectrum in the spatial frequency direction whereas the signal resides in a cone-shaped area. Figures 2a and 2b illustrate the $f-k$ spectrum of an unblended and a pseudodeblended common offset gather respectively. This property can be exploited by rejecting the parts of the spectrum where no signal is expected. In this way the incoherent blending noise is partly suppressed whereas the signal remains unaffected. Transforming back to the $x-t$ domain, the signal -being coherent- is now expected to have larger amplitude than the blending noise, hence a simple thresholding process can help keep only (part of) the coherent events of the gather. In the course of this iterative method, the threshold level is decreased until no further improvement is achieved. It is worth noticing that this type of filter can be coupled with a thresholding process in the $f-k$ domain. This process will keep only the major contributions of coherent events, resembling a POCS solver, see Abma and Kabir (2006).

$f-k_r-k_s$ filter

In this type of filter the whole data cube is treated simultaneously rather than treating different gathers separately. A three-dimensional Fourier transform is used to compute the $f-k_r-k_s$ spectrum of the dataset where k_r and k_s stand for the receiver and source wavenumber direction respectively. Similarly to the case of an $f-k$ transformed common offset gather, the blending noise extends outside the signal bandwidth. Figures 2c and 2d show the $k_s=0$ slice of an $f-k_r-k_s$ transformed data cube. Passing only certain source and receiver wavenumbers means that only certain angles of incidence and reflection angles are allowed. Under the horizontally layered earth assumption, such a filter imposes Snell's law to the data. Given that the interfering sources are not spaced very closely together, this can be a powerful tool for distinguishing between signal and blending noise since the interfering source illuminates a point in the subsurface from different angles than the signal source. As in the case of the $f-k$ filter, a thresholding process in either the frequency domain or the physical domain can follow in order to boost this coherence filter.

$\tau-p$ filter

A filter in the linear radon domain in combination with a thresholding process can also be used as a coherence-pass filter. Such a filter can be applied in any type of gather; here we apply it on common offset gathers. Figures 2e and 2f display a common offset gather in the $\tau-p$ domain. By choosing a certain range of ray parameters for the computation of the transformed data we are actually choosing the range of slowness values. This is essentially equivalent to the cone-shaped filter used in the $f-k$ domain. On top of that, this transform, in contrast to the previous two, offers control over the time axis. This allows for windowing in the time direction, hence focusing in areas which display high signal-to-blending noise ratio locally, i.e., the amplitude of the signal is significantly larger than the amplitude of the interference. This property can prove very beneficial especially during the first iterations of this deblending process. A thresholding process in the $\tau-p$ or the $x-t$ domain can follow in order to make sure that (almost) no blending noise leaks in the output.

EXAMPLE

A 2D blended dataset has been simulated based on unblended field data acquired at the Haltenbanken field in Norway. The dataset was acquired with spatial and temporal sampling intervals of 25 m and 4 ms, respectively. The sources were blended per two and they fire with small pseudo-random time delays. Figure 3a shows an unblended shot record. A shot record of the simulated blended survey, after pseudodeblending, can be seen in figure 3b. Notice the two different shot records that have been blended into one. The signal-to-blending noise ratio of this shot record is approximately 0 dB, i.e., the power of the signal is equal to the power of the blending noise.

The deblending procedure is carried out utilizing each time one of the three coherence filters presented in the method section. In order to facilitate a fair comparison between these three alternatives, the number of iterations was kept constant. The $f-k$ filter acted in the common offset domain and scored an overall improvement of 9.79 dB, see figure 3c. The $f-k_r-k_s$ filter scored 14.37 dB, see figure 3c, while the $\tau-p$ filter with an implementation in the common offset domain scored 18.11 dB, see figure 3e.

DISCUSSION AND CONCLUSIONS

An iterative deblending algorithm based on a coherence-pass filter was discussed. The three types of coherence-pass filters, $f-k$, $f-k_r-k_s$, and $\tau-p$, that were used inside the iterative deblending algorithm scored considerably different results. In this way the dependency of the method on the filter used was made clear. The $\tau-p$ filter outperformed the other two in the current example. However, claiming that it is the best choice for every type of deblending task is premature and more research and tests on different types of data need to be carried out to confirm this claim.

ACKNOWLEDGMENTS

We would like to thank Statoil for the permission to use and publish the marine dataset from the oilfield of Haltenbanken in Norway, and we would like to acknowledge the sponsors of the Delphi Consortium.

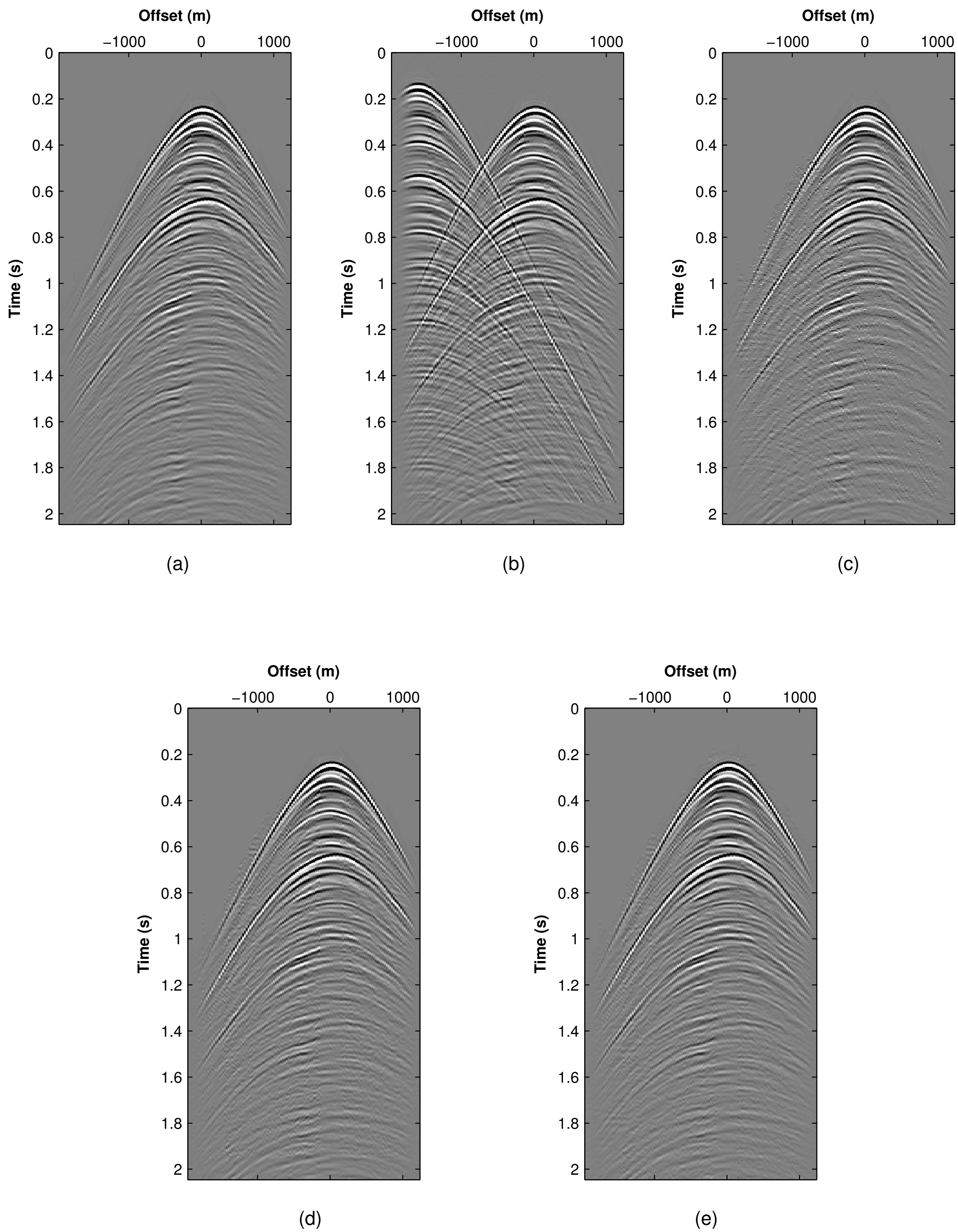

Figure 3: Unblended shot record 79, (a). The same shot record after blending and pseudodeblending, (b), deblending using the $f-k$ filter, (c), deblending using the $f-k_r-k_s$ filter, (d), and deblending using the $\tau-p$ filter, (e). 15 iterations were performed for all three cases.

REFERENCES

Abma, R., and N. Kabir, 2006, 3d interpolation of irregular data with a pocs algorithm: Geophysics, **71**, E91–97.

Abma, R., T. Manning, M. Tanis, J. Yu, and M. Foster, 2010, High quality separation of simultaneous sources by sparse inversion: 72nd Annual International Meeting, EAGE, Expanded Abstracts, B003.

Akerberg, P., G. Hampson, H. Richett, H. Martin, and J. Cole, 2008, Simultaneous source separation by sparse radon transform: 78th Annual International Meeting, SEG, Expanded Abstracts, 2801–2804.

Bagaini, C., 2006, Overview of simultaneous vibroseis acquisition methods: 76th Annual International Meeting, SEG, Expanded Abstracts, 70–74.

Beasley, C. J., R. E. Chambers, and Z. Jiang, 1998, A new look at simultaneous sources: 68th Annual International Meeting, SEG, Expanded Abstracts, 133–135.

Berkhout, A. J., 1982, Seismic migration, imaging of acoustic energy by wave field extrapolation, A. theoretical aspects: Elsevier.

———, 2008, Changing the mindset in seismic data acquisition: The Leading Edge, **27**, 924–938.

Berkhout, G., G. Blacquière, and E. Verschuur, 2010, Multi-scattering illumination in blended acquisition design: SEG Technical Program Expanded Abstracts, **29**, 1251–1255.

Dai, W., C. Boonyasiriwat, and G. T. Schuster, 2010, 3d multi-source least-squares reverse time migration: SEG Technical Program Expanded Abstracts, **29**, 3120–3124.

Doulgeris, P., A. Mahdad, and G. Blacquière, 2010a, Separation of blended data by iterative estimation and subtraction of interference noise: SEG Technical Program Expanded Abstracts, **29**, 3514–3518.

———, 2010b, Separation of blended impulsive sources using an iterative approach: 72nd Annual International Meeting, EAGE, Expanded Abstracts, B004.

Howe, D., M. Foster, T. Allen, I. Jack, D. Buddery, A. Choi, R. Abma, T. Manning, and M. Pfister, 2009, Independent simultaneous sweeping in libya -full scale implementation and new developments: 79th Ann. Internat. Mtg, Expanded Abstracts, Soc. of Expl. Geophys., 109–111.

Huo, S., Y. Luo, and P. Kelamis, 2009, Simultaneous sources separation via multi-directional vector-median filter: 79th Annual International Meeting, SEG, Expanded Abstracts, 31–35.

Kim, Y., I. Gruzinov, M. Guo, and S. Sen, 2009, Source separation of simultaneous source obc data: 79th Annual International Meeting, SEG, Expanded Abstracts, 51–55.

Mahdad, A., and G. Blacquière, 2010, Separation of blended impulsive sources using an iterative approach: 72nd Annual International Meeting, EAGE, Expanded Abstracts, B002.

Moore, I., 2010, Simultaneous sources - processing and applications: 72nd Annual International Meeting, EAGE, Expanded Abstracts, B001.

Moore, I., W. Dragoset, T. Ommundsen, D. Wilson, C. Ward, and D. Eke, 2008, Simultaneous source separation using dithered sources: 78th Annual International Meeting, SEG, Expanded Abstracts, 2806–2809.

Pecholcs, P. I., S. K. Lafon, T. Al-Ghamdi, H. Al-Shammery, P. G. Kelamis, S. X. Huo, O. Winter, J.-B. Kerboul, and T. Klein, 2010, Over 40,000 vibrator points per day with real-time quality control: opportunities and challenges: SEG Technical Program Expanded Abstracts, **29**, 111–115.