Machine learning based seismic data enhancement towards overcoming geophysical limitations

Nakayama, Shotaro; Blacquière, Gerrit

DOI
10.2118/202710-MS

Publication date
2020

Document Version
Final published version

Published in
Abu Dhabi International Petroleum Exhibition and Conference 2020, ADIP 2020

SPE-202710-MS

Machine Learning Based Seismic Data Enhancement Towards Overcoming Geophysical Limitations

Shotaro Nakayama, INPEX Corporation; Gerrit Blacquière, Delft University of Technology

This paper was prepared for presentation at the Abu Dhabi International Petroleum Exhibition & Conference to be held in Abu Dhabi, UAE, 9 – 12 November 2020. Due to COVID-19 the physical event was changed to a virtual event. The official proceedings were published online on 9 November 2020.

Abstract

Acquisition of complete data, i.e., unblended, well-sampled and broadband data, is technically desirable. Obviously, such a scenario is prohibitively expensive to realize. To deal with economic considerations in a seismic survey without seriously compromising data quality, we propose a machine-learning approach that offers an opportunity to acquire incomplete data, i.e., blended, sparsely-sampled and narrowband data, while still benefitting from being able to process complete data. In this study, we utilize a deep convolutional neural network. The incomplete data are fed into the applied network that simultaneously performs suppression of blending noise, reconstruction of missing traces and extrapolation of low frequencies such that prediction of the complete data is attainable. We validate the performance of the proposed method using both synthetic and field datasets. Acquisition scenarios implemented to generate incomplete datasets impose a significant reduction of data size in the frequency-space domain. Despite the limited information available in the input data, the prediction results obtained from both numerical and field data examples clearly confirm that the proposed machine-learning approach is capable of dealing with deficiencies in the incomplete data and subsequently deriving the complete data of sufficient quality. In addition to suppression of blending noise and reconstruction of missing traces, no discernible difference in prediction errors between preexisting and extrapolated frequencies is observed, which is hardly realizable with existing geophysics-based approaches. As a consequence, the proposed scheme allows for optimal data enhancement even when seismic acquisition is performed in a blended, sparsely-sampled and narrowband fashion.

Introduction

One may consider that the geophysically ideal seismic acquisition involves perfect spatial sampling, i.e., regularly and densely distributed detectors and sources, such that the Nyquist sampling theorem is sufficiently satisfied for the target frequency range. Additionally, it is desirable to use a spatially consistent source response covering a broad bandwidth at each shot grid. Nevertheless, this scenario is hardly achievable due to operational and economic considerations. To deal with the trade-off between technical and business objectives, it is worthwhile to implement strategies that can mitigate the compromise on data quality while minimizing the acquisition effort.

In recent years, various studies have demonstrated the effectiveness of compressive sensing that offers a novel spatial sampling method. The technique allows for the reduced field measurements in a random fashion, which do not necessarily obey the Nyquist rate, and subsequently aims at recovering the desired signal (Herrmann, 2010; Mosher et al., 2012; Millis, 2018). Since the spatial distribution of detectors and sources is one of the key factors determining the operational effort, acquisition geometries that makes use of the principle of compressive sensing leads to enhancing the acquisition efficiency. Blended acquisition, or sometimes referred to as simultaneous source acquisition, utilizes two or more sources activated at (almost) the same time. Blended acquisition can also be regarded as a part of compressive sensing (Lin and Hermann, 2009). Unlike conventional, unblended acquisition, the technique permits the overlap of multiple source wavefields in time and space. This leads to a significant improvement in acquisition efficiency without adversely affecting data quality (Berkhout, 2008; Bouska 2010; Abma et al., 2012; Nakayama et al., 2012). Alternatively, it is capable of enhancing subsurface coverage without increasing project cost and time.

To make compressed field measurements technically justifiable, one needs to pay proper attention towards a subsequent data recovery step, such as deblending and data reconstruction. To deal with such an underdetermined system, either the use of low-rank approximation or sparsity promoting program in some transform domain(s) has proven to be an effective way (Herrmann and Hennenfent, 2008; Oropeza and Sacchi, 2011; Kutscha and Verschuur, 2012). Although its applicability has been rigorously studied, the requirement of an iterative procedure makes a data recovery problem computationally expensive. Furthermore, the compressed signal in the transform domain may not necessarily explain all the complexities of the subsurface geology, which potentially leads to imperfection in the recovery result.

Contributions of low frequency components to data quality has been well recognized in various aspects, such as illumination of deep targets, suppression of the wavelet sidelobes, estimation of absolute properties, and convergence of full-waveform inversion to a global minimum (Ten Kroode et al., 2013, Berkhout and Blacquière, 2017). However, generating low frequency energy is a cumbersome task in the field as it requires dedicated equipment as well as extra source effort (Dellinger et al., 2016; Wei et al., 2018). This unavoidably makes seismic acquisition more costly and time-consuming. Hence, the estimation of low frequencies during data processing, referred to as low-frequency extrapolation in this study, is an attractive way in both business and operational aspects. Although there have been several studies towards low frequency extrapolation (Wu et al., 2014; Zhang et al., 2017), it is not straightforward to obtain an intrinsic relationship between recorded and missing frequencies.

In recent years, the application of machine-learning (ML) has become increasingly popular including in the geoscience domain. For example, several attempts utilizing an ML approach have been made for a deblending or data reconstruction problem and have demonstrated comparable performance to existing geophysical approaches (Siahkoohi et al., 2019; Sun et al., 2020). Additionally, once a network has been trained, the prediction result can be obtained in a very efficient manner. Some recent studies using synthetic data attempted to extrapolate low frequencies (Sun and Demanet, 2018; Ovcharenko et al., 2019). However, these mentioned tasks have been so far treated separately. Our primary objective is, therefore, to investigate the applicability of an ML approach that aims at predicting unblended, well-sampled and broadband data, defined as complete data, from blended, sparsely-sampled and narrowband data, defined as incomplete data. This means that the proposed scheme tries to deal with attenuation of blending noise, reconstruction of missing traces and extrapolation of missing low frequencies in a simultaneous fashion. We validate the ML based data recovery using both numerical and field data examples.

Method

In this study, we apply a deep convolutional neural network based on the so-called U-Net architecture (Ronneberger et al., 2015). Figure 1 is a schematic illustrating the applied network architecture, consisting of pairs of encoding and decoding blocks as well as a center block in between. In our application, the incomplete data in the time-space domain are fed into the trained neural network, and then the complete data in the time-space domain are obtained. Through encoders, the input data is down sampled with a max pooling layer (Nagi et al., 2011), allowing key features to be extracted. These compressed features are then up sampled through subsequent decoders with a transposed convolutional layer (Dumoulin and Visin, 2016). There are skip pathways directly connecting the encoder and decoder blocks. This helps the network to capture and transfer detailed or subtle information which may be smeared through down sampling and up sampling processes. Each block employs sets of a convolutional layer (LeCun et al., 1998) followed by a rectified linear unit (Hahnloser et al., 2000) and a batch normalization layer (Ioffe and Szegedy, 2015). We also implement residual learning in each block to mitigate the degradation problem, i.e., decaying prediction accuracy with the network depth (He et al., 2016).

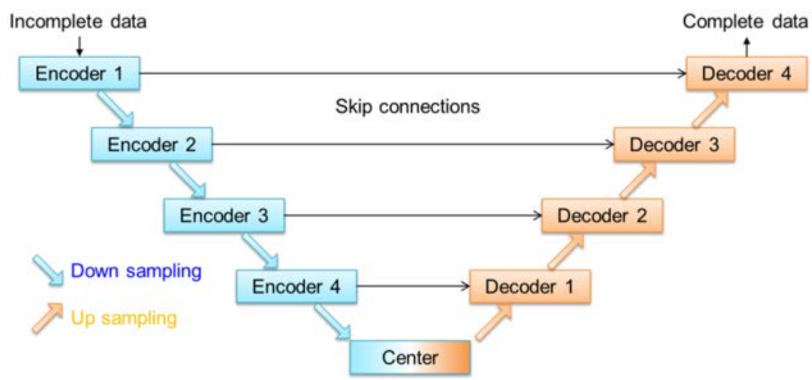

Figure 1—Network architecture of the applied convolutional neural network, consisting of sets of encoding and decoding blocks along with skip pathways directly connecting each encoder and decoder.

Results

We generate 20,000 subsurface models, each comprising of three anticlinal reflectors. For each model, we arbitrarily alter the subsurface structures, i.e., depth and geometry of each reflector, as well as subsurface properties, i.e., propagation velocity between each reflector and reflectivity of each interface. Based on these subsurface scenarios, we derive 20,000 complete datasets with a 20 m detector and source interval using full wave field modelling (Berkhout, 2014). To obtain incomplete datasets, we irregularly decimate 50% of detectors and 50% of sources. We also apply a blending fold of two (Berkhout and Blacquière, 2013) and random time dithering. Low frequencies are also missing in the incomplete data. The applied acquisition scheme consequently leads to a significant reduction of the data size in the space-frequency domain with respect to the complete data. The change in the data size is indicative of survey duration and cost that the incomplete data can save. 19,000 complete-incomplete data pairs are arbitrarily selected as training sets, while the remaining 1,000 pairs are used as testing sets.

Figure 2 shows one of the recovery results from the testing sets. Here, we selected one complete-incomplete data pair yielding the median result in terms of prediction errors, which is assumed to be the representative outcome of the applied ML scheme. As compared to the complete data considered as a reference (Figures 1a and 1b), the incomplete data (Figures 2c and 2d) notably exhibit blending noise and acquisition gaps in the time-space domain. The corresponding frequency-wavenumber domain clearly shows a lack of low frequencies. This indicates that a significant amount of information is absent in the incomplete data. Despite the aforementioned deficiencies in the incomplete data, the trained network successfully suppresses blending noise, reconstructs missing traces and extrapolates low frequencies (Figures 2e and 2f). The difference plots between modeled and predicted complete data notably show no frequency dependency in prediction errors (Figures 2g and 2h). This means that the low frequency components, which are not available in the input data, are well predicted. Consequently, the predicted data attain comparable quality to the reference data.

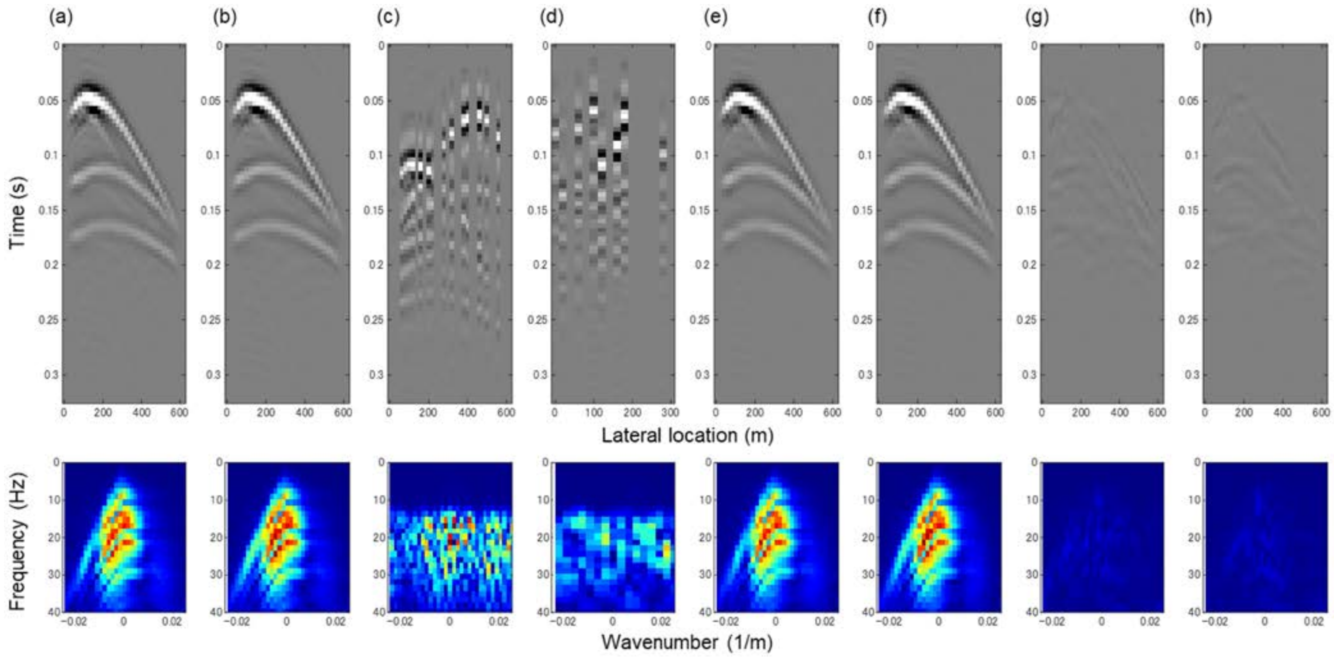

Figure 2—Prediction result (synthetic data example). Top figures show data in the time-space domain while bottom ones are data in the frequency-wavenumber domain. Modeled complete data (reference): (a) common shot gather and (b) common detector gather. Incomplete data: (c) common shot gather and (d) common detector gather. Predicted complete data: (e) common shot gather and (f) common detector gather. Difference between reference and predicted complete data: (g) common shot gather and (h) common detector gather.

We also applied the ML approach to a field data set, acquired offshore Norway. A subset of this field data with 25 m detector and source sampling is used to generate 12,000 training sets, i.e., pairs of complete-incomplete data. As in the numerical example, for incomplete datasets, we irregularly decimate both detectors and sources by 25%. Low frequencies are also missing. The applied blending scheme employs a blending fold of two and random time dithering. A testing set is derived from a portion of the filed data in a different area, meaning that there is no overlap between training and testing datasets.

Figure 3 shows the data recovery result using the field data. Similar to the numerical example, the ML scheme simultaneously performs deblending, trace reconstruction and low frequency extrapolation, of sufficient quality. Although the input data employ a narrow bandwidth, the level of prediction errors is fairly comparable for the whole frequency range (Figure 4d). This field data example further confirms the validity of the applied ML approach. It is also noteworthy that, with a trained network, prediction of the incomplete data can be quickly done for both numerical and field data examples.

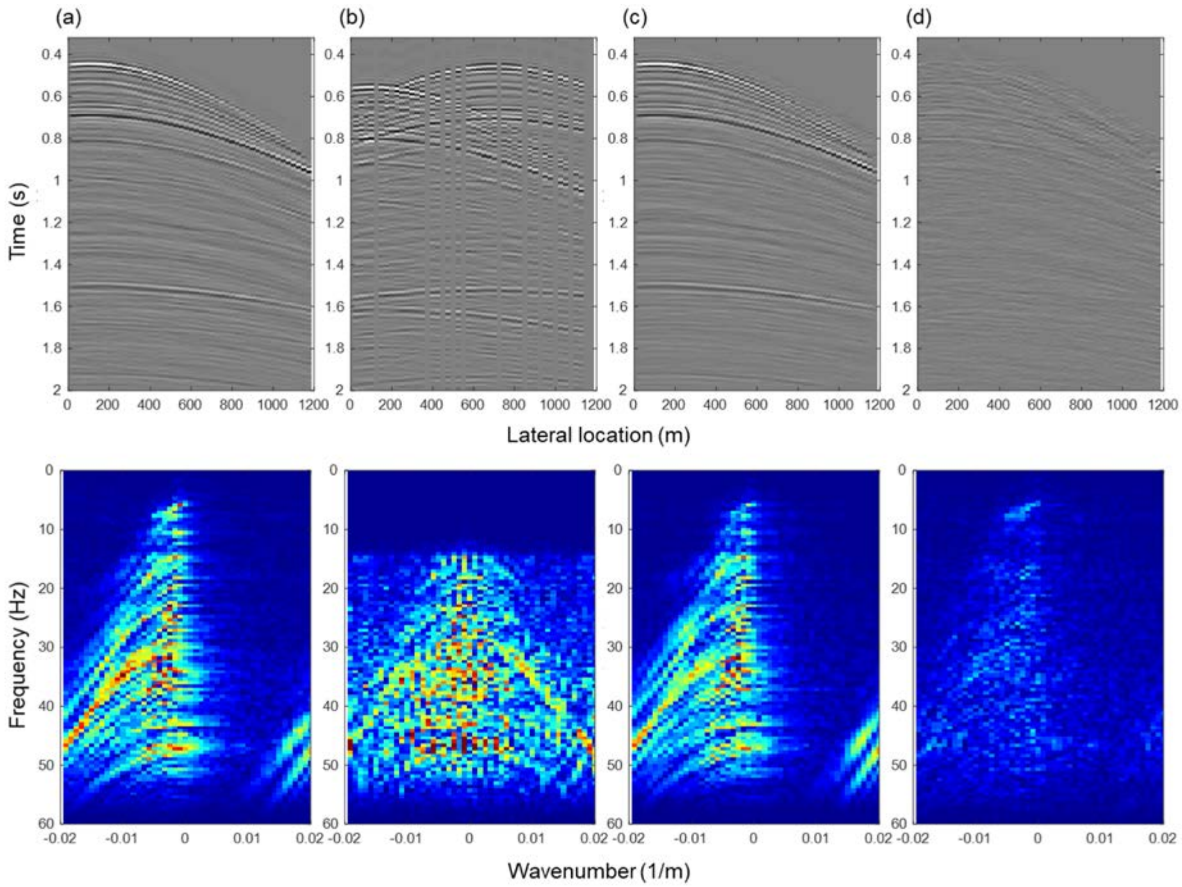

Figure 3—Prediction result (field data example). Top figures show data in the time-space domain while bottom ones are data in the frequency-wavenumber domain. (a) Complete data (reference). (b) Incomplete data. (c) Predicted complete data. (d) Difference between reference and predicted complete data.

Conclusions

In this study, we apply a deep convolutional neural network based on the U-Net architecture in the framework of supervised learning to predict complete data from incomplete data. The applied network aims at simultaneously performing suppression of blending noise, reconstruction of missing traces and extrapolation of low frequencies. We validate the proposed ML approach using synthetic and field data sets. Although the acquisition scenarios applied to generate the incomplete data sets significantly compress the data size in the frequency-space domain, the recovery results clearly confirm that the proposed approach effectively derives the complete data for both numerical and field data examples. One of the remarkable outcomes in the applied method is that there is no discernible difference in prediction errors between extrapolated frequencies and preexisting frequencies, which is hardly achievable with existing geophysical methods. Although further investigations are required, the ML based data recovery scheme potentially allows field operations to be performed in a significantly efficient way while providing satisfactory data quality.

Acknowledgement

The authors would like to express their appreciation to all the sponsors of DELPHI consortium. Special acknowledgement goes to Equinor for providing us with the field data. Shotaro Nakayama is thankful to INPEX Corporation for sponsoring his research at Delft University of Technology.

References

Abma, R., Zhang, Q., Arogunmati, A., and Beaudoin, G. (2012). An overview of BP's marine independent simultaneous source field trials. In SEG Technical Program Expanded Abstracts 2012 (pp. 1–5). Society of Exploration Geophysicists.

Berkhout, A. J. (2008). Changing the mindset in seismic data acquisition. *The Leading Edge*, **27** (7), 924–938.

Berkhout, A. J. (2014). An outlook on the future of seismic imaging, Part I: forward and reverse modelling. *Geophysical Prospecting*, **62** (5), 911–930.

Berkhout, A. J., and Blacquière, G. (2013). Effect of noise in blending and deblending. *Geophysics*, **78** (5), A35–A3.

Berkhout, A. J., Blacquière, G., and Verschuur, D. (2017). Enlarging the bandwidth of seismic images. In SEG Technical Program Expanded Abstracts 2017 (pp. 180–185). Society of Exploration Geophysicists.

Bouska, J. (2010). Distance separated simultaneous sweeping, for fast, clean, vibroseis acquisition. *Geophysical Prospecting*, **58** (1), 123–153.

Dellinger, J., Ross, A., Meaux, D., Brenders, A., Gesoff, G., Etgen, J., and Harper, M. (2016). WolfspaR, an "FWI-friendly" ultralow-frequency marine seismic source. In SEG Technical Program Expanded Abstracts 2016 (pp. 4891–4895). Society of Exploration Geophysicists.

Dumoulin, V., and Visin, F. (2016). A guide to convolution arithmetic for deep learning. arXiv preprint arXiv: 1603.0728.

Hahnloser, R. H., Sarpeshkar, R., Mahowald, M. A., Douglas, R. J., and Seung, H. S. (2000). Digital selection and analogue amplification coexist in a cortex-inspired silicon circuit. *Nature*, **405** (6789), 947–951.

He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770–778).

Herrmann, F. J. (2010). Randomized sampling and sparsity: Getting more information from fewer samples: *Geophysics*, **75**. WB173–WB187, 13.

Hennenfent, G., and Herrmann, F. J. (2008). Simply denoise: Wavefield reconstruction via jittered undersampling. *Geophysics*, **73** (3), V19–V28.

Ioffe, S., and Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. arXiv preprint arXiv:1502.03167.

Kutscha, H., and Verschuur, E. (2012). Data reconstruction via sparse double focal transformation: An overview. *IEEE Signal Processing Magazine*, **29** (4), 53–60.

LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, **86** (11), 2278–2324.

Lin, T. T., and Hellmann, F. J. (2009). Designing simultaneous acquisitions with compressive sensing. In 71st EAGE Conference and Exhibition incorporating SPE EUROPEC 2009. European Association of Geoscientists & Engineers.

Millis, K. (2018). Compressive seismic imaging: A land-acquisition case study and operational considerations. In SEG Technical Program Expanded Abstracts 2018 (pp. 112–115). Society of Exploration Geophysicists.

Mosher, C. C., Kaplan, S. T., and Janiszewski, F. D. (2012). Non-uniform optimal sampling for seismic survey design. In 74th EAGE Conference and Exhibition incorporating SPE EUROPEC 2012. European Association of Geoscientists & Engineers.

Nagi, J., Ducatelle, F., Di Caro, G. A., Ciresan, D., Meier, U., Giusti, A., Nagi, F., Schmidhuber, J., and Gambardella, L. M. (2011). Max-pooling convolutional neural networks for vision-based hand gesture recognition: *IEEE*, 342–347.

Nakayama, S., Mercado, G., Benson, M. A., Belaid, K., and Garden, M. (2015). Field-wide implementation of time and distance separated source techniques on a 3D OBC survey offshore Abu Dhabi, UAE. *First Break*, **33** (4).

Oropeza, V., and Sacchi, M. (2011). Simultaneous seismic data denoising and reconstruction via multichannel singular spectrum analysis. *Geophysics*, **76** (3), V25–V32.

Ovcharenko, O., Kazei, V., Kalita, M., Peter, D., and Alkhalifah, T. (2019). Deep learning for low-frequency extrapolation from multioffset seismic data. *Geophysics*, **84** (6), R989–R1001.

Ronneberger, O., Fischer, P., Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234–241). Springer, Cham.

Siahkoohi, A., Kumar, R., and Hellmann, F. J. (2019). Deep-learning based ocean bottom seismic wavefield recovery. In SEG Technical Program Expanded Abstracts 2019 (pp. 2232–2237). Society of Exploration Geophysicists.

Sun, H., and Demanet, L. (2018). Low frequency extrapolation with deep learning. In SEG Technical Program Expanded Abstracts 2018 (pp. 2011–2015). Society of Exploration Geophysicists.

Sun, J., Slang, S., Elboth, T., Larsen Greiner, T., McDonald, S., & Gelius, L. J. (2020). A convolutional neural network approach to deblending seismic data. *Geophysics*, **85** (4), WA13–WA26.

Ten Kroode, F., Bergler, S., Corsten, C., de Maag, J. W., Strijbos, F., and Tijhof, H. (2013). Broadband seismic data—The importance of low frequencies. *Geophysics*, **78** (2), WA3–WA14.

Wei, Z., Criss, J., Bull, A., Liang, F., and Wu, Y. (2018). The low-frequency seismic vibrator: design and experimental verification. *First Break*, **36** (1), 77–84.

Wu, R. S., Luo, J., and Wu, B. (2014). Seismic envelope inversion and modulation signal model. *Geophysics*, **79** (3), WA13–WA24.

Zhang, P., Han, L., Xu, Z., Zhang, F., and Wei, Y. (2017). Sparse blind deconvolution based low-frequency seismic data reconstruction for multiscale full waveform inversion. *Journal of Applied Geophysics*, **139**, 91–108.