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Nakayama, S.; Blacquière, G.; Ishiyama, T.

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Survey Design Towards Optimum Reflectivity and Velocity Estimates Directly from Blended and Irregularly-Sampled Data

S. Nakayama[1,2]*, G. Blacquière[1], T. Ishiyama[2,3]

[1] Delft University of Technology; [2] INPEX Corporation; [3] ADNOC

Summary

The application of blended acquisition along with irregular acquisition geometries contributes to the economic perspective of a seismic survey. The joint migration inversion scheme is capable of directly processing the data acquired in this way, i.e., without deblending or data reconstruction, and of subsequently estimating both reflectively and velocity models. The workflow proposed in this study aims to design the source blending operator as well as detector and source sampling operators. The approach iteratively computes these parameters in such a way that the quality of reflectivity and velocity models, which are directly estimated from blended and irregularly-sampled data, is adequate. The workflow integrates a genetic algorithm and a convolutional neural network to derive optimum parameters. Bio-inspired operators enable the simultaneous update of the blending and sampling operators. To relate the choice of survey parameters to the performance of a joint migration inversion, we utilize a convolutional neural network. The applied network architecture discards suboptimal solutions among newly generated ones. Conversely, it passes optimal ones to the subsequent step, which successfully enhances the efficiency of the proposed approach. The resultant acquisition scenario yields a notable enhancement in both reflectivity and velocity estimates attributed solely to the choice of survey parameters.

Introduction

The application of blended acquisition has drawn considerable attention due to its ability to provide high-quality seismic data in a cost-effective and timely manner (Berkhout, 2008). Efficient acquisition geometries, e.g., with a reduced number of irregularly deployed detectors and sources, also known as compressive sensing (Herrmann, 2010), considerably contribute to the business aspect. For the implementation of these techniques, the previously mentioned deficiency in recorded data needs to be addressed through subsequent processing steps such as deblending and/or data reconstruction.

Alternatively, a least-squares migration scheme can produce the subsurface reflectivity directly from blended data, i.e., without the need of deblending, by iteratively minimizing the misfit between the observed and the estimated blended data (Tang and Biondi, 2009). Nemeth (1999) showed that the technique is also capable of producing optimum subsurface images even when the input data suffer from coarse and/or irregular spatial-sampling. In addition to imaging, blended data can be directly used for full waveform inversion which attempts to minimize the misfit between the observed data and the forward-modeled blended data (Florez et al., 2016). Krebs et al (2009) and Boonyasiriwat and Schuster (2010) demonstrated that the use of random time shifts in blended shots and random selections of sources to be inverted are effective means to enhance the inversion results. These studies then infer that design of survey parameters responsible for the source blending and acquisition geometries potentially contributes to an effective estimate of subsurface properties when one aims to directly use blended and irregularly-sampled data.

This paper, hence, proposes an iterative scheme to derive optimum survey parameters that can provide satisfactory reflectivity and velocity estimates via a joint migration inversion (JMI) (Berkhout, 2014). The technique iteratively estimates both a high-resolution reflectivity and a migration velocity model by updating two independent operators, **R** and **W**, each responsible for reflection and propagation respectively. We extend the standard implementation of JMI to directly use blended and irregularly sampled data. This is then incorporated into the proposed survey-design scheme. The workflow uses errors in reflectivity and velocity estimates from the JMI process for a given survey design. They are subsequently evaluated by another system based on the integration of a genetic algorithm (GA) and a convolutional neural network (CNN) to update blending and sampling operators. Numerical examples utilizing the dispersed source array (DSA) concept (Berkhout, 2012) outline the results of the proposed workflow.

Survey design workflow

Berkhout (2008) proposed the theoretical framework of source blending by introducing a blending operator, $\mathbf{\Gamma}$, containing the blending information such as which sources to be blended and the blending codes applied to each source. This enables us to obtain blended data, $\mathbf{P}'$, according to the following formulation in the frequency domain:

$$\mathbf{P}' = \mathbf{P\Gamma} = \mathbf{DXS\Gamma}. \tag{1}$$

D and **S** are detector and source matrices containing the information on their spatial locations at the surface. **X** is the Earth transfer operator responsible for subsurface reflection and propagation properties, meaning that **X** can be approximated from **R** and **W** (Berkhout, 2014). Equation 1 indicates that any blending and spatial-sampling schemes can be modeled by designing **D**, **S** and $\mathbf{\Gamma}$.

JMI iteratively minimizes the residue between observed and estimated data from its forward modeling engine, the so-called full wavefield modeling (FWMod). In the JMI process, the data misfit can be translated to errors in **R** and **W**. Resultant updated operators are then attributed respectively to the reflectivity and velocity models. In this study, our minimization scheme in JMI can be formulated as:

$$J = \sum_{\omega} \left\| \mathbf{P}' - \langle \mathbf{P}' \rangle \right\|_2^2 = \sum_{\omega} \left\| \Delta \mathbf{P}' \right\|_2^2, \tag{2}$$

where the angle brackets indicate estimations. This indicates that we can directly estimate both reflectivity and velocity models using blended and irregularly sampled data.

Figure 1 illustrates our survey-design workflow, which iteratively performs the following three steps to find **D**, **S** and **Γ** while we assume **R** and **W** to be available in this study. The latter makes our survey design subsurface dependent. The first step (blue box in Figure 1) is FWMod to obtain **P**′ from known subsurface properties, **R** and **W**, as well as estimated survey parameters, **D**, **S** and **Γ**. The second step (red box in Figure 1) is the application of JMI to obtain <**R**> and <**W**> from **P**′. In our workflow, we formulate a multi-objective minimization based on the residue between **R** and <**R**> as well as **W** and <**W**>:

$$\mathbf{j}=\left[J_{\mathrm{R}},J_{\mathrm{W}}\right]^{T}=\left[\sum_{\omega}\left\|\hat{\mathbf{R}}-\langle\hat{\mathbf{R}}\rangle\right\|_{2}^{2},\sum_{\omega}\left\|\hat{\mathbf{W}}-\langle\hat{\mathbf{W}}\rangle\right\|_{2}^{2}\right]^{T}=\left[\sum_{\omega}\left\|\Delta\hat{\mathbf{R}}\right\|_{2}^{2},\sum_{\omega}\left\|\Delta\hat{\mathbf{W}}\right\|_{2}^{2}\right]^{T}, \quad (3)$$

where $\mathbf{j}$ is the objective function vector containing errors in $\hat{\mathbf{R}}$ and $\hat{\mathbf{W}}$. $\hat{\mathbf{R}}$ is the reflectivity information from **R** converted to time such that any undesired effects from errors in **W** to J_{R} can be avoided. $\hat{\mathbf{W}}$ represents velocity fields converted from **W**. In the third step, **D**, **S** and **Γ** are updated in the green box. Newly generated operators are subsequently fed into the next iteration. The procedure stops once **j** becomes sufficiently small, or the maximum number of iterations is exceeded.

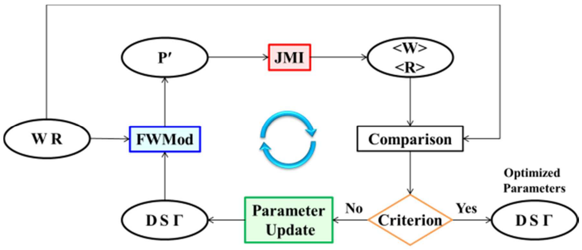

Figure 1 *The overall iterative survey-design workflow. FMWod in the blue box generates blended and irregularly sampled data (**P'**). JMI in the red box estimates reflectivity and velocity models using a given design. GA and CNN embedded into the green box update the survey parameters.*

Survey parameter update

In this study, we integrate a GA and a CNN for the survey-design workflow (Figure 2). Using genetic operators, we update **D**, **S** and **Γ** simultaneously. The performance of JMI for a given survey design is assigned as its objective function vector described in equation 3. The solution is iteratively updated when the GA generates a design with a smaller misfit. However, in this case, we need to evaluate all the solutions to obtain their objective function values even when the GA provide suboptimal solutions which do not contribute to the subsequent iteration, making our approach time consuming.

To handle this challenge, we integrate a CNN that accounts for the selection of survey designs prior to the JMI process. Our network architecture is designed to classify whether survey parameters for a given design can satisfy predetermined thresholds based on J_{R} and J_{W}. Until this criterion is satisfied, genetic operators repeatedly produce new survey parameters which are subsequently evaluated by the CNN. Only solutions that pass the classification step in the CNN go to the JMI process to derive **j** from estimated reflectivity and velocity models. This enables only effective designs to be used for the subsequent iteration, leading to efficient convergence as compared to a standard GA. At each iteration, we also train the CNN using the actual JMI results. We apply a five-fold cross-validation allowing us to utilize all samples for both testing and training purposes, and then to assess the predictive performances of the models. The best model among five is subsequently used in the next iteration. After a certain number of iterations, our workflow achieves stable and acceptable performance along with an insignificant difference in classification accuracies between training and testing sets. It is worth noting that an imperfection in the classification result has no direct impact on the update of survey parameters, as it is done primarily on the basis of the actual performance of JMI.

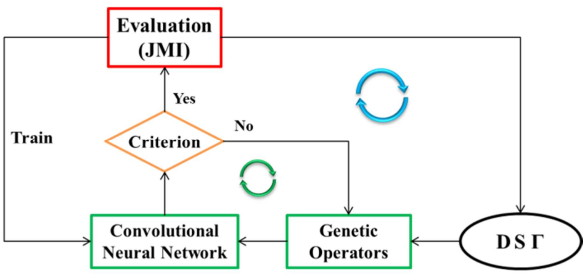

Figure 2 *The scheme focusing on the procedure to optimize **D**, **S** and **Γ**. The GA repeatedly produces these operates till the criterion in the CNN is met. They are subsequently fed into JMI to obtain estimates of reflectivity and velocity. The CNN is trained at each iteration using actual JMI results.*

Numerical examples

We numerically simulate acquisition scenarios that incorporate the blended DSA concept. Figure 3a shows a shot gather that exemplifies our blending and spatial-sampling schemes. It contains two active shots with a 1000 m separation having different blending codes such as activation times and frequency bands. Figures 3b-c illustrate parameters related to the detector and source sampling. In our example, 50 detectors are irregularly distributed at the surface in our model with a lateral length of 2000 m. Three types of DSA source units having different spectral properties, activation times and spatial-sampling requirements are also irregularly distributed. In Figure 3, these parameters are randomly derived. In addition to the optimized design obtained from the proposed approach, we show a result that employs survey parameters generated by a random realization from a discrete uniform distribution for a comparison purpose. Both cases employ the same number of detectors and DSA source units. Two sources are activated simultaneously. Parameters used in JMI are kept constant. In the optimized design, we update the spatial distributions of detectors and three types of DSA sources along with their activation times ranging from 0 s to 0.256 s.

Figures 4a-b show the true subsurface responses used in this study. The model contains a lens-shaped high-velocity body above three horizontal reflectors. Figures 4c-d show the initial reflectivity and velocity models in JMI which exhibit no indication of true geological features. Figures 4e-h show a comparison of the JMI results between the two cases. The random design leads to several oblique lineaments, causing some jitter on the reflectors. The lateral velocity variation, particularly beneath the high-velocity body, adversely affects the kinematics of wave propagation. It consequently generates undesired structural undulations on three reflectors. The optimized design, however, attains notable enhancement in the JMI results. The lens-shaped body can be clearly delineated in both reflectivity and velocity estimates. Reduction of artifacts improves the coherence of reflectors. It also achieves a robust estimate of the velocity model, which enables all the reflectors to be recovered close to their actual locations. This clearly demonstrates that our approach is capable of optimizing survey parameters to enhance reflectivity and velocity estimates using blended and irregularly-sampled data.

Conclusions

The iterative scheme introduced in this study aims to design survey parameters responsible for the source blending and the spatial sampling of sources and detectors. The proposed workflow integrates a GA and a CNN to derive optimum blending and sampling operators in an affordable computation time. The resultant acquisition scenario can enhance the performance of JMI directly processing blended and irregularly-sampled data without the need of deblending or data reconstruction.

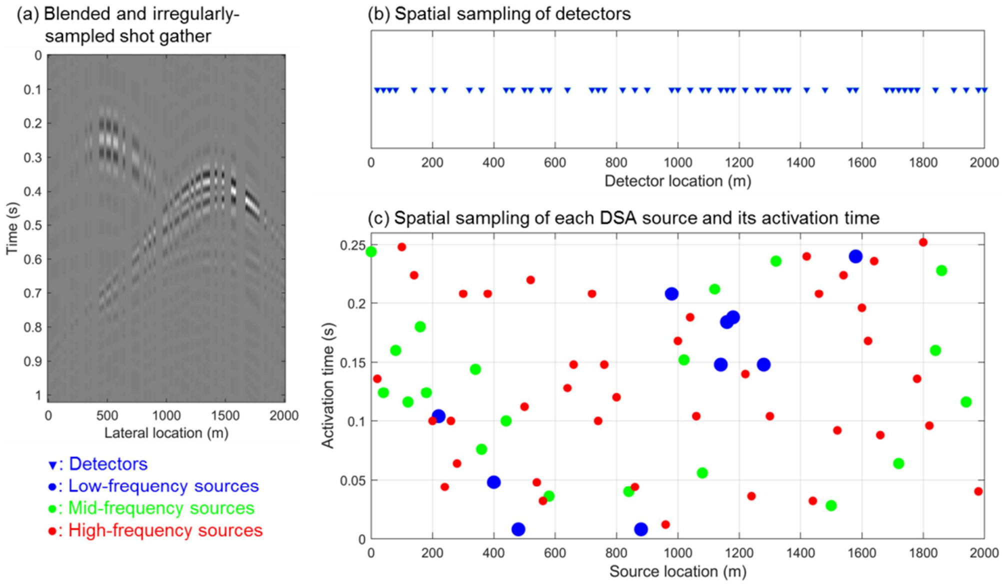

Figure 3 *Blended DSA acquisition scenarios used in this study.*

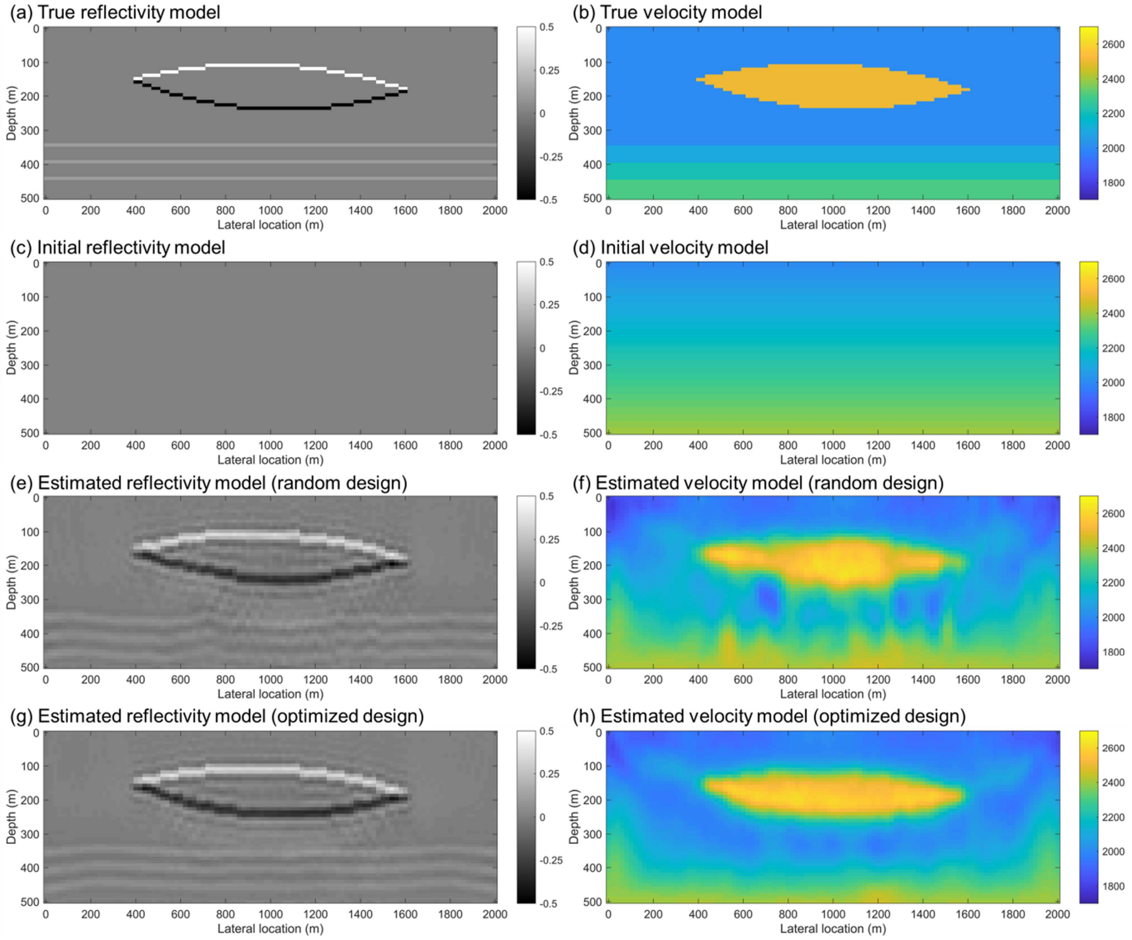

Figure 4 *Comparison of JMI results between two different design schemes. The notable enhancement in the performance of JMI due solely to the choice of survey parameters is easily recognizable.*

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References

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

Berkhout, A. J. 2012. Blended acquisition with dispersed source arrays. *Geophysics*, **77**, A19–A23.

Berkhout, A. J. 2014. Review Paper: An outlook on the future of seismic imaging, Part III: Joint Migration Inversion. *Geophysical Prospecting*, **62**, 950-971.

Boonyasiriwat, C. and Schuster, G. T. 2010. 3D multisource full-waveform inversion using dynamic random phase encoding. 80th SEG annual meeting, Expanded Abstracts, 1044-1049.

Florez, K. A., Mantilla, J. G. and Ramirez, A. B. 2016. Full Waveform Inversion (FWI) in time for seismic data acquired using a blended geometry. 2016 XXI Symposium on Signal Processing, Images and Artificial Vision (STSIVA), 1-5.

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

Krebs, J. R., Anderson, J. E., Hinkley, D., Neelamani, R., Lee, S., Baumstein, and Lacasse, M.-D. 2009. Fast full-wavefield seismic inversion using encoded sources. *Geophysics*, **74**, WCC177-WCC188.

Nemeth, T., Wu, C. and Schuster, G. T., 1999. Leastsquares migration of incomplete reflection data. *Geophysics*, **64**, 208-221.