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Optimum seismic acquisition geometry design with the help of artificial intelligence

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Summary

Acquisition geometry design aims at finding the most affordable acquisition geometry that satisfies the objectives of the seismic survey. The parameters of an acquisition geometry can be specified in terms of the number of sources and detectors, their location, the blending parameters and the DSA (dispersed source array) parameters. In our acquisition geometry design, we include the effects of the (expected) subsurface, i.e., we assume the subsurface to be known. Consequently, the ideal data set – carpet shooting and carpet detection – can be modeled. A practical data set can be considered to be a subset of this ideal one. Acquisition design comes down to determining the optimum subset. Following compressive sensing, this subset is sparse and irregular. As a quality measure, we apply decompression (deblending and interpolation) to the subset, which leads to an estimate of the ideal data set, and then compare this estimate with the known ideal data set. The difference is the residue that should satisfy a predefined quality criterion. This procedure is the inner loop of a genetic algorithm. A CNN (convolutional neural network) is trained to improve the efficiency of the genetic algorithm by enhancing the effectiveness of each next generation. Furthermore, the solution space is limited to reduce the amount of computations needed. Finally, in this application it is acceptable to end up in a local minimum. The latter corresponds to an acquisition geometry that fully satisfies the quality and economic criteria (although some acquisition geometry may exist that provides even better results). Our design method leads to results that are better than those obtained with randomized acquisition geometries.

Introduction

Acquisition geometry design aims at finding the optimum acquisition geometry – in terms of efficiency, economics, safety, etc. – that satisfies the objective regarding the seismic image – in terms of image resolution, accuracy of reflectivity information, signal-to-noise ratio, etc.

Obviously, one way to achieve an improved efficiency and better economics is to collect less data, i.e., to sample sources and detectors sparsely, e.g., by deploying compressive sensing (Herrmann et al., 2011; Mosher et al., 2014, Allegar et al., 2017). In compressive sensing the spatial sampling of the sources and detectors is irregular to improve the results of sparse data reconstruction (Campman, 2017).

A special case of compressive sensing, which further improves the efficiency as well as the data quality, is blending, also called simultaneous source acquisition (Beasley, 2008; Berkhout, 2008).

A technology aiming at an improved data quality, in particular with regard to the (ultra) low frequencies (Ten Kroode et al., 2013) is the DSA concept introduced by Berkhout (2012). In this concept there are various dedicated source types, each transmitting a narrow part of the spectrum, together producing the full temporal bandwidth.

In this paper, the design of a geometry for a blended, irregularly-sampled, DSA acquisition is discussed.

Theory

The Earth transfer function described by matrix **X** can be considered to be the ideal seismic data set with unit sources and unit detectors everywhere, i.e., 'dense carpet shooting' and 'dense carpet detection', where the size of the 'carpet', i.e., the aperture, is considered sufficiently large for the purpose. In the monochromatic case, each column of **X** contains the response due to one source being recorded by all detectors. If multiple frequencies are involved, each frequency component has its own unique **X**. In the practice of seismic data acquisition, **X** is never measured because sources and detectors are not everywhere, and they are not ideal: they do have a certain temporal and spatial frequency response (sensitivity, directivity). Instead, data matrix **P** is acquired. In the case of a stationary acquisition geometry, the relation between the measured data **P** and the Earth transfer matrix **X** is given by:

$$\mathbf{P}(z_d;z_s) = \mathbf{D}(z_d)\mathbf{X}(z_d,z_s)\mathbf{S}(z_s), \tag{1}$$

where, matrices **D** and **S** are the detector and source matrix, respectively (Berkhout, 1983). They contain the mentioned detector and source properties, as well as their locations. The depth levels of the detectors and sources are given by z_d and z_s, respectively. The size of **P** is n_d by n_s, being the number of detectors and sources, respectively. In the case of a non-stationary acquisition geometry, **P** can be found by simply setting the traces that have not been acquired to zero. In other words, the actual acquisition geometry can be found from the ideal acquisition geometry by applying a mask corresponding to the traces that have been actually acquired:

$$\mathbf{P}(z_d;z_s) = \mathcal{M}_{\mathbf{DS}}\left[\mathbf{X}(z_d,z_s)\right], \tag{2}$$

where $\mathcal{M}_{\mathbf{DS}}$ is the mask, representing a non-linear operator that clears the traces from **X** that were not acquired by the current acquisition geometry and leaves the ones that were acquired, see the example in Figure 1.

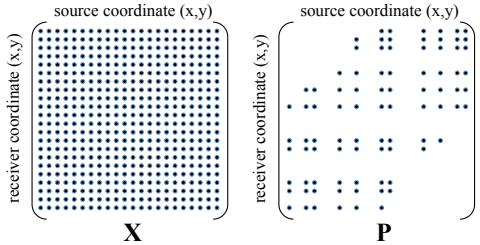

Figure 1: Acquired data set **P** is a subset of ideal data set **X**

Optimum acquisition design using AI

In addition, it contains the directivity and sensitivity properties of the sources and detectors for the particular frequency. Equation (2) indicates that **P** is a subset of **X**.
From this theory it is clear that the ultimate acquisition geometry would be such that **P** = **X**. In that case, the information from the subsurface contained in **P** is the maximum we could ever get from the seismic method. However, this acquisition geometry would be extremely expensive and inefficient. Therefore, in practice, the number of non-zero elements in **P** is small compared to **X**. Obviously, the question is: is it still possible to retrieve all the required subsurface information from **P**.
To answer this question, one could try to obtain an estimate <**X**> of **X** from **P**. To get such an estimate, one would need to create the traces-that-were-never-measured by interpolation and/or regularization (data reconstruction). Note that this decompression step can be realized by using technologies developed in compressive sensing.
Today, the benefits of blended acquisition (also called simultaneous-source acquisition) have been recognized in the industry (Abma et al., 2015; Nakayama et al., 2018). Blending increases the efficiency of the acquisition and data quality, while reducing the cost and HSE exposure. Blending can be formulated as:

$$\mathbf{P}'(z_d;z_s)=\mathbf{P}(z_d;z_s)\Gamma(z_s)=M_{\mathbf{DS}}\left[\mathbf{X}(z_d,z_s)\right]\Gamma(z_s), \quad (3)$$

where $\Gamma(z_s)$ is the blending matrix, containing the sources to be blended and their blending codes, e.g., time dithers, or any amplitude and/or phase encoding. In the case of blended acquisition, we have to estimate <**X**> from **P'**, which means that, apart from interpolation and/or regularization, deblending must be performed as well.
As equation (3) is in the frequency domain, it is suited to represent DSA acquisition without modifications.

Acquisition design can now be defined as follows: find the $M_{\mathbf{DS}}$ and $\Gamma(z_s)$ that lead to a 'good' <**X**> obtained from **P'**.
A 'good' <**X**> means that the residue – being the difference between <**X**> and **X** – is smaller than a certain predefined maximum while the economic and efficiency requirements have been met. To compute the residue, **X** must be known. It comes down to having prior knowledge about the subsurface. E.g., this knowledge can be available from previous acquisitions. The ideal data represented by **X** can then be obtained by modeling, e.g., by finite-difference of finite-element modeling.
A flow-chart of the iterative algorithm for acquisition geometry design is shown in Figure 1. Although the algorithm structure is quite simple, there are some issues that need to be addressed. The first is the large number of possible acquisition geometries. There are many options for the spatial (x,y) location of each source and detector.

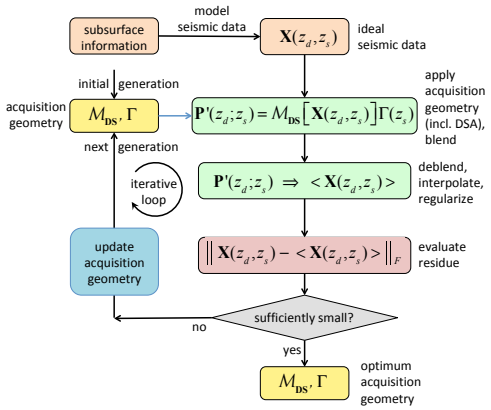

Figure 2: Flow-chart for optimum acquisition design

This is also the case for the activation time of each source (or, more generally, its blending code). These properties make the solution space huge. The second issue is related to the computation of the estimate <**X**> from **P'**, which corresponds to a deblending and interpolation/regularization procedure. This decompression step is computationally intensive and since it is part of the inner loop of the iterative algorithm, it makes the method rather expensive.

To address these issues, the following approach is proposed.
(1) A genetic algorithm is used to update the parameters at each iteration. To reduce the size of the solution space, a bio-inspired technique called Repeated Encoding Sequence was applied (Nakayama et al., 2018). A consequence of limiting the solution space is that the obtained solution -most likely- will not be the global minimum. Fortunately, unlike in many other optimization schemes, a 'good' local minimum is fully acceptable in the case of acquisition geometry design, i.e., 'good' in terms of a sufficiently small residue. The fact that a better geometry may exist with an even smaller residue (or 'cheaper' but with the same residue) doesn't reduce the applicability of the local-minimum solution.
(2) To increase the efficiency of the computation of <**X**>, artificial intelligence is used. A convolutional neural network (CNN) has been developed that helps the genetic algorithm to create an effective next generation of possible solutions. The network is trained to predict whether or not a particular parent candidate will be sufficiently 'fit for survival', i.e., whether or not the residue will be sufficiently small. Only a candidate that has been classified as 'fit' is allowed to become a parent of the next generation. If not, the genetic algorithms creates an alternative candidate, which will undergo the same procedure. The 'update acquisition geometry' module is shown in more detail in Figure 2.

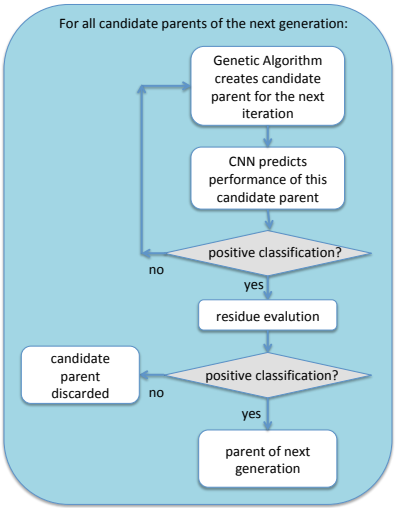

Figure 3: Flow-chart for the module 'update acquisition geometry' module with the convolutionan neural network, see Figure 2.

The efficiency increase is obtained because the candidate parents of the next generation have already been classified to be 'fit' in a computationally affordable way by the CNN. They are high potentials. It means that no expensive computation time is wasted in estimating <**X**> from acquisition geometries that are likely to give high residues. This leads to fewer iterations. The structure of the CNN classifier used in our work is given in
Figure 4.

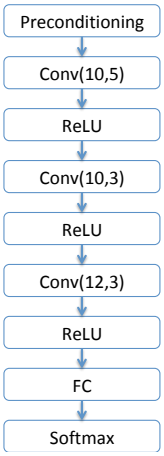

Figure 4: The structure of the convolutional neural network used to classify candidate parents of the next generation, see also Figure 3. Conv(n,m) stands for convolution with an n-by-m coefficient filter, ReLu stands for rectified linear unit, FC stands for fully connected.

The 'Conv' layers connect neighboring elements of a member of the current layer to each other. The 'ReLU' layers provide the required non-linearity to the network by their thresholding property: they pass positive values while clearing negative ones. The result after several of such layers are high-level features. Finally, the 'FC' layer combines these features in a non-linear way to do the classification, while the 'Softmax' layer provides the probability distribution of the final classification. For more information on CNN's the reader is referred to the literature. Examples of the use of CNNs for seismic applications are Waldeland and Solberg (2017) and Wang et al. (2018).

Example

In this example a 2D irregular acquisition geometry is designed, based on the Marmousi subsurface model. First the ideal data set **X** was computed using finite-difference modeling. The spatial source and detector intervals were chosen to be 10 m to avoid spatial aliasing.
Then some choices regarding the geometry to be designed were made. It was decided to reduce the number of detectors by 20% to reduce cost. The acquisition follows the DSA concept by deploying four source types: ultralow-, low-, mid- and high-frequency sources, their share of the total number of sources being $^{1}/_{15}$, $^{2}/_{15}$, $^{4}/_{15}$ and $^{8}/_{15}$, respectively. The total number of sources remained the same. The spatial distribution of the detectors and the sources of the various types is irregular. The acquisition geometry is stationary.

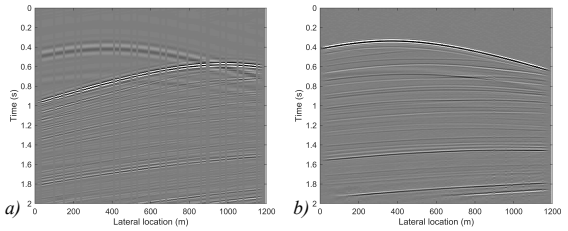

Figure 5: In *a)* a shot record from **P'** is shown (DSA acquisition, blending fold of 2, 20% detector reduction). In *b)* the corresponding record of <**X**> , which now contains the full bandwidth, is shown.

An example of a blended shot record of **P'** according to the acquisition geometry obtained via the design procedure as outlined, is shown in Figure 5a. It contains the response of a low-frequency source and of a high-frequency source. No other source types were deployed at this particular lateral location. It also shows the 20% reduction in detectors. The record of <**X**> at a shot location corresponding to the location of the low-frequency source in Figure 5a, is shown in Figure 5b. It was obtained from data matrix **P'** after deblending and interpolation and it contains the full seismic bandwidth.
The number of iterations was limited to 800. The result shown in Figure 5b was compared with the mean result obtained from 800 random realizations of the acquisition parameters, representing an arbitrary irregular acquisition geometry. Furthermore, the result was compared with the best result of these 800 random realizations, representing a

'lucky shot'. The objective function value, i.e., the value of the residue $\|\mathbf{X} - \langle\mathbf{X}\rangle\|_F$ (where subscript F refers to the Frobenius norm) of this comparison is shown in Figure 6.

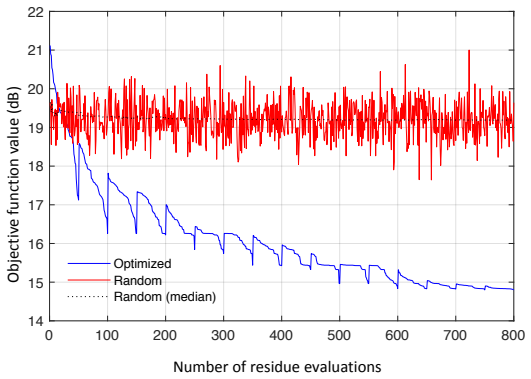

Figure 6: Objective function value versus realization number (for the random acquisition geometries) or residue eveluation number (for the optimization method).

The residue of the mean of 800 realizations for this Marmousi model is 19.2, the best result of 800 realizations is 17.6, whereas the residue of the optimized geometry after 800 evaluations (16 iterations, 50 members per generation) is as low as 14.8. This example clearly demonstrates that designing the irregularity is superior to an arbitrary random acquisition design. This finding corresponds well with the conclusion drawn by Campman et al. (2017) who state that sparse, irregular geometries can be optimized for reconstruction.

An example of an optimized acquisition geometry is given in Figure 7. terms of the locations of the detectors (shown in Figure 7a), and the locations, activation times as well as source types involved (shown in Figure 7b).

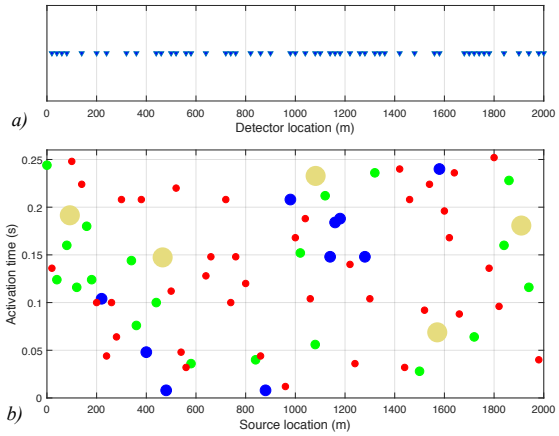

Figure 7: Example of acquisition design. In a) the detector locations are shown. In b) the source locations, source activation times, and source types are shown (from smallest to largest dots: red - high frequency, green - mid frequency, blue - low frequency, yellow - ultralow frequency).

Concluding remarks

In acquisition design, the aim is to find the most affordable acquisition geometry that answers the questions related to the subsurface geology. To that end, the acquisition geometry must be optimized in terms of the number of sources and detectors, their location, the blending parameters and the DSA parameters. In our acquisition geometry design, we assume the subsurface to be known. Consequently, the ideal data set – carpet shooting and carpet detection – is known as well. A practical candidate acquisition geometry is characterized by sparsely and irregularly sampled sources and detectors. As a quality measure, we first estimate the ideal data from data modeled according to a candidate acquisition geometry, by interpolation and deblending, and then compare this estimate with the known ideal data set. The difference is the residue that should satisfy a predefined criterion. This procedure is the inner loop of a genetic algorithm and the total number of possible acquisition geometries is huge. Therefore, computational efficiency is very important. To improve the efficiency of the genetic algorithm, a convolutional neural network is trained to enhance the effectiveness of each next generation. Furthermore, the solution space is limited to reduce the required number of computations. Fortunately, in this application it is acceptable to end up in a local minimum. The latter corresponds to an acquisition geometry that fully satisfies the criteria with respect to quality and economy, although some acquisition geometry may exist that provides even better results.

The results obtained by optimizing a sparse, irregular acquisition geometry are considerably better than the results obtained with randomized sparse, irregular acquisition geometries.

Instead of computing the residue $\|\mathbf{X} - \langle\mathbf{X}\rangle\|_F$, with the aim of reconstructing the ideal data set, one could alternatively replace this by the residue $\|\mathbf{P}_{good} - \langle\mathbf{P}_{good}\rangle\|_F$, where $\mathbf{P}_{good}$ is a data set that is sufficiently well sampled for the purpose. E.g., this could be a 'trusted' traditional survey design, see also Mosher et al. (2014). Using $\mathbf{P}_{good}$ rather than $\mathbf{X}$ relaxes the requirements, which in turn is expected to result in a more efficient acquisition geometry.

Finally, a further improvement in the computational efficiency of the method is expected by exploiting the fact that $\mathbf{X}$ (or $\mathbf{P}_{good}$) is known in this particular application, e.g., one could use this information to define a smart starting model in the decompression step.

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