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Survey Designing for Blended Acquisition with Irregularly Sub-Sampled Geometries

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Summary

We introduce a workflow to derive survey parameters responsible for source blending as well as spatial sampling of detectors and sources. The proposed workflow iteratively performs the following three steps. The first step is application of blending and sub-sampling to an unblended and well-sampled data. We then apply a closed-loop deblending and data reconstruction enabling a robust estimate of a deblended and reconstructed data. The residue for a given design from this step is evaluated, and subsequently used by genetic algorithms (GAs) to simultaneously update the survey parameters related to both blending and spatial sampling. The updated parameters are fed into a next iteration till they satisfy given stopping criteria. We also propose repeated encoding sequence (RES) used to form a parameter sequence in GAs, making the proposed designing workflow computationally affordable. We demonstrate the results of the workflow using numerically simulated examples that represent blended dispersed source array data. Difference attributable only to a way to design parameters is easily recognizable. The optimized parameters yield clear improvement of deblending and data reconstruction quality and subsequently provide optimal acquisition scenarios. Additionally, comparison among different optimization schemes illustrates ability of GAs along with RES to efficiently find better solutions.

Introduction

The application of blended acquisition has drawn considerable attention due to its ability to improve operational efficiency as well as data quality and HSE performance. Furthermore, acquisition of less data contributes to the business aspect while the desired data density is still realizable via subsequent data reconstruction. Thus, the combined implementation of these technologies potentially enhances the value of a seismic survey. One way to encourage this is to minimize any imperfection in deblending and data reconstruction at the processing. On top of this, one may derive survey parameters that enable a further improvement of these processes, as targeted in this study.

In existing blended acquisition schemes, irregularity or randomness is often embedded into survey parameters such as a random time delay on each source. This makes the source wave field incoherent in at least one of the sorting domains that allows for effective source separation (Baardman et al., 2013). Herrmann (2010) showed that spatial sub-sampling of data in an irregular fashion is a key element of compressive sensing, leading to optimal signal recovery. Despite the potential benefits of blending and sub-sampling, designing a survey incorporating those techniques is rather intricate as irregularity inherently requires numerous selections of survey parameters unlike acquisition in a regular manner.

In this study, we introduce a workflow to design a seismic survey that incorporates both blending and irregular sub-sampling of detectors and sources. The workflow includes a closed-loop approach allowing for a robust deblending and data reconstruction. The residue for a given survey design is evaluated and subsequently used by another system based on genetic algorithms (GAs), allowing for a simultaneous update of blending and sampling operators. Repeated Encoding Sequence (RES) is proposed and implemented to form a parameter sequence for GAs, making the size of the search space manageable. The results of the proposed workflow are outlined in blended Dispersed Source Array (DSA) data (Berkhout, 2012).

The forward and inverse models

Berkhout (2008) proposed the theoretical framework of source blending by introducing a blending operator, $\mathbf{\Gamma}$ containing the blending information such as sources to be blended and their activation times. This enables us to obtain a blended record, $\mathbf{P}'$, from an unblended data, $\mathbf{P}$, according to:

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

Here $\mathbf{D}$ and $\mathbf{S}$ are matrices related to the detectors and the sources, containing information on their spatial locations at the surface. $\mathbf{X}$ is the Earth's transfer function containing entire subsurface impulse responses. It represents unblended seismic data with perfect spatial sampling of sources and detectors. If we successfully remove the effects of $\mathbf{D}$, $\mathbf{S}$ and $\mathbf{\Gamma}$ from $\mathbf{P}'$, we obtain an accurate estimate $\langle\mathbf{X}\rangle$ of $\mathbf{X}$. Our approach aims to design $\mathbf{D}$, $\mathbf{S}$ and $\mathbf{\Gamma}$ such that this removal is possible, i.e., such that an effective deblending and data reconstruction are realizable. Since we deal with acquisition design, $\mathbf{X}$ is known.

Figure 1 is a schematic illustrating our survey-design workflow that iteratively performs the following three steps. The first step (blue box in Figure 1) is the forward modeling (going from $\mathbf{X}$ to $\mathbf{P}'$ using $\mathbf{D}$, $\mathbf{S}$ and $\mathbf{\Gamma}$), i.e., application of blending and sub-sampling to the unblended and well-sampled seismic data as described in equation (1). The second step (red box in Figure 1) is the application of deblending (going from $\mathbf{P}'$ to $\langle\mathbf{P}\rangle$) and data reconstruction (going from $\langle\mathbf{P}\rangle$ to $\langle\mathbf{X}\rangle$) using sparsity and coherency constraints (Ishiyama et al., 2017). By rewriting the blended source matrix $\mathbf{S\Gamma}$ as $\mathbf{S}'$, we write a pseudo inverse model as:

$$\mathbf{D}^H(\mathbf{DD}^H)^{-1}\mathbf{P}'(\mathbf{S}'^H\mathbf{S}')^{-1}\mathbf{S}'^H = \mathbf{X}\,, \tag{2}$$

where superscript H denotes the Hermitian conjugate. Since both deblending and data reconstruction are under-determined problems with more unknowns than equations, a least-squares criterion is used to minimize the following objective function:

$$J = \left\|\mathbf{P}' - \langle\mathbf{P}'\rangle\right\|^2, \tag{3}$$

To solve the inverse problem, we apply a closed-loop approach that iteratively estimates an unblended and reconstructed data $\langle\mathbf{X}\rangle$, that is used to derive $\langle\mathbf{P}'\rangle$ to the objective function in equation (3).

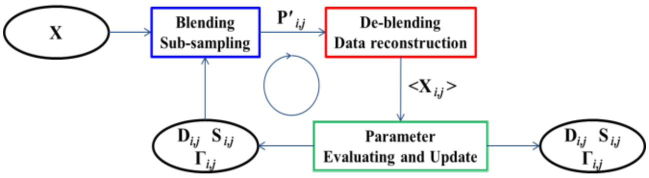

Figure 1. Proposed workflow consisting of three steps in blue: forward model for blending and sub-sampling; red: inverse model for deblending and data reconstruction; and green: parameter evaluation and update with GAs.

Survey design with genetic algorithms

Holland (1975) originated the concept of GAs and demonstrated how the theory of evolution can be exploited for optimization problems. Since then, numerous successful applications of GAs have been developed in various domains. The third step of our approach (green box in Figure 1) utilizes GAs to update estimates of **D**, **S** and **Γ**. As mentioned, we consider **X** to be known. A sequence of parameter sets, considered as biological chromosomes, is evolved (optimized) through a set of stochastic operators in GAs by minimizing the following objective function:

$$F_{i,j} = \left\| \mathbf{X} - \left\langle \mathbf{X}_{i,j} \right\rangle \right\|^2 , \tag{4}$$

where i and j are the number of individual solution and generation respectively. At first, a set of parameter sequences, called initial population, is randomly generated across the given problem space. Once their objective functions are obtained, parental solutions are selected using a roulette-wheel scheme. In a given generation, an expected selection probability of the ith solution according to its objective function is defined as:

$$G[\langle \mathbf{X}_i \rangle] = f_i / \sum_{i=1}^{m} f_i \;\; \text{with} \;\; f_i = \exp(\beta F_i / \min_{i \in m} F_i), \tag{5}$$

where β is a dimensionless parameter controlling the diversity in the selection. A sequence contains different parameter sets, responsible for blending and sampling operators. Since each set employs different lengths and constraints, we apply single-crossover per parameter set. Followed by mutation that locally yet randomly modifies a solution, a new population replaces the parental one based on elitism, allowing us to preserve some better parental solutions in a new generation. The updated parameters are fed into a next iteration until the objective function in equation (4) is sufficiently small.

Whilst GAs generally have the ability to handle large problem sizes, a reduction of the parameter space is still worthwhile to make the proposed workflow practical. In this respect, we introduce RES that makes use of DNA as an analogy to form a parameter sequence in GAs. Figure 2a exemplifies a way to generate RES using 20 binary numbers. We first create a main code whose length has to be 2×N times as long as the minimum one (Step 1). This code is then divided in two halves to make 2 base codes (Step 2). These are flipped to create 2 more base codes (Step 3). The 4 base codes are finally combined in a predetermined order to form a parameter sequence that resembles a chain of 4 nucleobases in DNA (Step 4). Additionally, it is well known that DNA has a double helix structure in which one nucleobase bonds with a different one, referred to as base pairs. We also use this analogy for blended acquisition. We predefine base pairs; e.g., a base code 1 bonds only with 4 while 2 only

(a)

Step 1	Main code: 01001011011100101010
Step 2	Base codes 1&2: 0100101101&1100101010
Step 3	Base codes 3&4: 1011010010&0101010011
Step 4	Primary source: 1342432123 14 ----- Blended source: 4213123432 41 -----

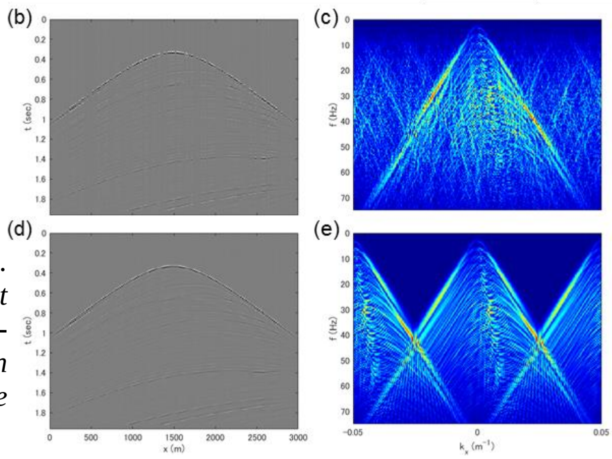

Figure 2 RES. (a) shows steps to generate RES. (b) and (c) are an irregularly sub-sampled shot record with RES in time-space and frequency-wave number domains. (d) and (e) are one with regular sub-sampling. Both cases have the same number of detectors.

bonds with 3. Once the parameters of a primary source are defined, the ones of another source to be blended are automatically defined (Step 4), ensuring that they possess different properties.

With RES, the optimization deals with a single main code only, leading to a significant reduction of the parameter space. Although 4 base codes are repeated, each one holds a random-like feature, and they irregularly appear according to a predetermined order. Sub-sampled seismic data with RES therefore employs a property of irregularity that creates Gaussian-noise like aliasing artefacts (Figures 2b-c) unlike regularly sub-sampled data (Figures 2d-e). This allows the deblending and reconstruction processes to effectively estimate the desired signals and separate these from undesired events.

Results

As summarized in Table 1, 4 blended acquisition scenarios are numerically simulated using a synthesized 2D Marmousi data set consisting of 120 detectors and 120 sources with the sampling interval being 10 m. We incorporate the DSA concept using 4 source types (Table 2), each having its own spectrum and spatial distribution; e.g., 25% means keeping 1 out of 4 shots. To introduce irregularity in the operators, we use a random realization from a discrete uniform distribution. A time delay ranging from 0 to 256 ms is applied to each scenario. Sub-sampled cases employ detector decimation, keeping 4 out of 5 detectors. In scenario 4, we apply our method; i.e., we optimize the spatial distribution of detectors and 4 DSA sources as well as the time shift applied to each source.

	D and **S**	**Γ**
1	Well-sampled	Random
2	Regularly sub-sampled	Random
3	Randomly sub-sampled	Random
4	Optimally sub-sampled	Optimized

Table 1. Sub-sampling and blending operators of 4 acquisition scenarios

	Bandwidth	Well-sampled	Sub-sampled
1	2-10 Hz	12.5%	6.7%
2	4-20 Hz	25%	13.3%
3	8-40 Hz	50%	26.7%
4	16-80 Hz	100%	53.3%

Table 2. Bandwidths and spatial distributions of 4 DSA sources

Figure 3 shows before (top row) and after (bottom row) deblending and reconstruction for 4 scenarios. As expected, scenario 1, having neither detector nor source decimation, achieves the highest signal to noise ratio (SNR) of 25.7 dB determined by $20\log(|X|^2/|X-\langle X\rangle|^2)$. Although 3 subsampled cases have the same blending performance indicator (Berkhout and Blacquière, 2014), and the same number of detectors and sources, they exhibit notable differences, solely due to the way to design the operators. The optimized design has low blending and reconstruction noise, leading to the high SNR of 21.8 dB, as compared to 16.1 and 17.7 dB of scenarios 2 and 3. This indicates that the quality of deblending and data reconstruction depends on the choice of blending and sampling parameters. Our approach helps to find optimum solutions via a simultaneous update of these parameters.

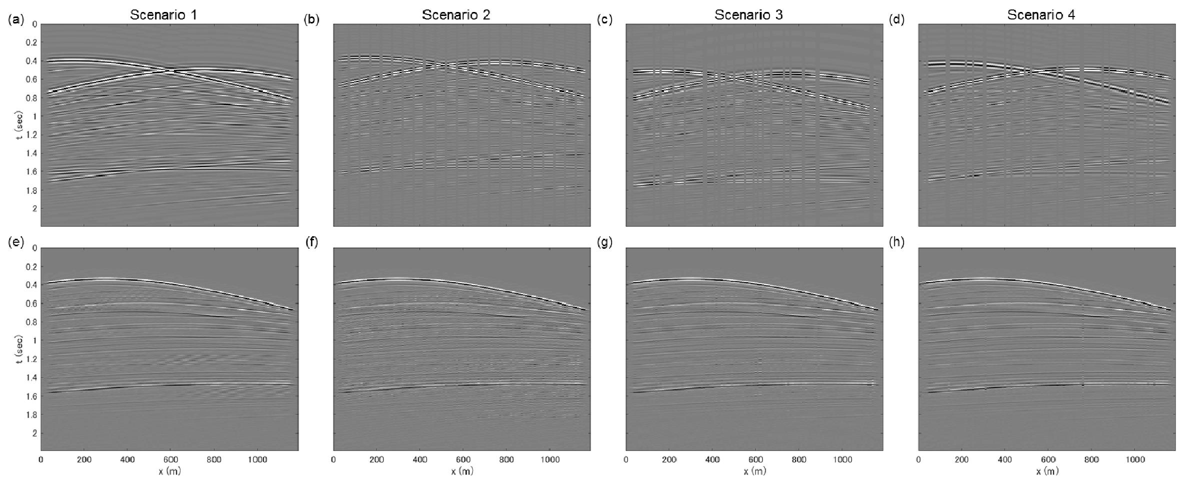

Figure 3. Before (top row) and after (bottom row) deblending and data reconstruction for different acquisition scenarios. Their SNR values are 25.8, 16.1, 17.7 and 21.8 dB respectively.

Figure 4 shows a comparison among 4 optimization schemes: 1) GAs with RES (the same as scenario 4 in table 1); 2) GAs without RES; 3) Monte Carlo simulation (MSC) with RES; and 4) MSC without RES. We apply the same number of realizations to equalize the computation time. As compared to the use of a random realization (17.7 dB of scenario 3 in table 1), each approach obtains a higher SNR: 21.8, 20.3, 20.5 and 19.2 dB respectively. Additionally, a notable difference among 4 schemes is also recognisable. Within the limited number of realizations, application of RES leads to a higher SNR for both GAs and MCS cases by the reduction of problem space. Comparison with MCS confirms the ability of an evolution process in GAs to quickly reach optimum survey parameters. GAs with RES hence allow us to design blending and spatial sampling operators in an effective and efficient manner.

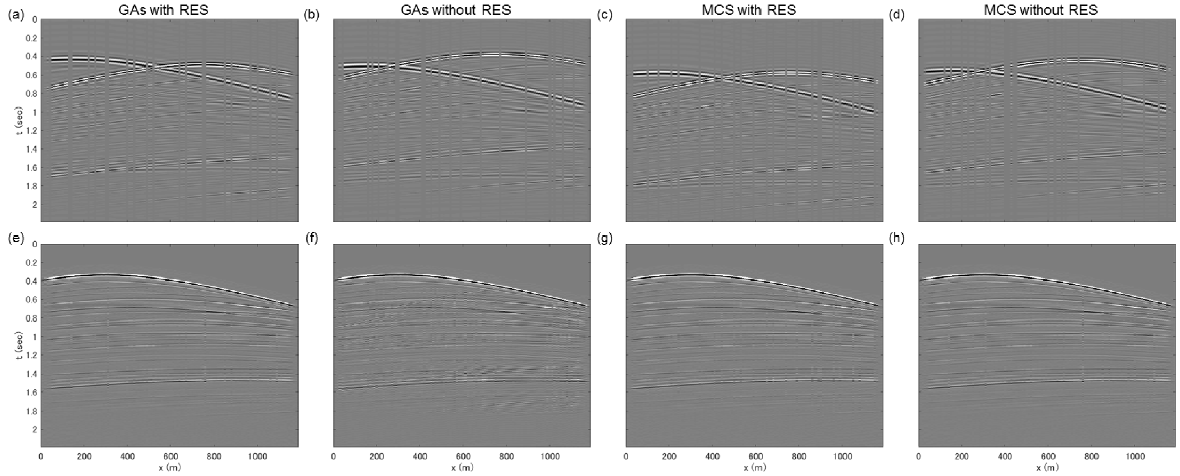

Figure 4. Before (top row) and after (bottom row) deblending and data reconstruction for different optimization schemes: (a) GAs with RES; (b) GAs without RES; (c) MCS with RES; and (d) MCS without RES. Their SNR values are 21.8, 20.3, 20.5 and 19.2 dB respectively.

Conclusions

We introduced a workflow to design a seismic survey, including the parameters for source blending and sub-sampling of detectors and sources. The approach iteratively performs a simultaneous update of the blending and sampling operators. This leads to the optimum acquisition scenario, allowing for the enhancement of deblending and data reconstruction quality. The implementation of GAs and RES helps us to find better solutions from a large parameter space within affordable computation time.

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