Bi-objective optimization for seismic survey design

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Summary

I applied a bi-objective optimization strategy to search the best seismic survey design in illumination and cost senses. Due to the conflicting goals of obtaining a good subsurface illumination at the lowest possible cost it is not possible to obtain an optimum survey in both senses simultaneously, but instead it is possible to get a set of surveys, called Pareto Front, that shows the trade-off between these conflicting objectives. As a result, the Pareto Front could be used as a decision tool to tune quality versus cost. I used the mixed-integer, free-derivative, nonlinear optimization algorithm called Particle Swarm Optimization and Mesh Adaptive Direct Search. The Particle Swarm Optimization part is used to escape local minima while the mixed-integer part is used to deal with integer aspects of a seismic survey design like the number of receivers and sources, to name but a few.

Introduction

Seismic surveys are commonly designed by following a set of rules based on the CMP assumption (Cordsen et al., 2000) and by performing seismic modelling on a small set of survey proposals to measure the imaging quality of each one of them.

In Ozdenvar et al. (1996) it is proposed to model a complete survey before it is acquired to evaluate the survey characteristics prior to field deployment. Some authors have proposed optimization schemes for designing seismic surveys that automatically look for a design that minimizes certain criteria. In Liner et al. (1998) the possibility of optimizing the survey design is exposed by using an objective function based on the common rules of survey design. In the work of Alvarez et al. (2004) an objective function based on the quality of the illumination of the subsurface target is used instead.

There are many optimization techniques that can be used in survey design but the ones that can escape local minima, manage integer variables and optimize multiple variables at the same time are preferred due to the nature of the problem. Particle Swarm Optimization (Eberhart and Kennedy, 1995) and Mesh Adaptive Direct Search (Audet and J. E. Dennis, 2006) are two optimization algorithms that have been used together (PSO-MADS) in oil field plan optimization (Isebor et al., 2014). The first one is a global search method while the second is a local optimizer. These algorithms have potential in survey design for their managing of integer variables and the possibility of performing a bi-objective optimization of target illumination and survey cost at the same time.

Method

The survey design bi-optimization is composed of the following steps:

1. Choose a set of parameters that describe the acquisition with their upper and lower bounds. Some of these parameters could be integers while others are real numbers.
2. Define the illumination and cost objective functions.
3. These functions will guide the PSO-MADS algorithm in the search of seismic surveys with high illumination quality and low cost.
4. The Pareto Front that will be produced by the bi-optimization will show the trade-off between illumination and survey cost.

Survey parametrization

Conventional seismic surveys can be described by an extensive set of parameters. Here I concentrate in only six of them, although the method allows to use more. The parameters I use are first and last source positions, source and receiver spacing, and first and last live receivers. To simplify, all surveys are regular split spread.

Model extension or block exploration size is what constraints first and last source positions. For source and receiver space I define a minimum spacing, Δr, and allow receiver space Δg to be an integer multiple of Δr, that is, only Δr, $2\Delta r$, . . . , $N\,\Delta r$, where the maximum receiver spacing, N , is also set by the user. In the same way, the source spacing Δs is limited to a finite number of multiples of the receiver spacing. Similarly, the first and last live receivers in a shot can take an integer between 1 and a maximum number of receivers per shot, M , that is also defined by the user.

Illumination objective function

The approach used here is based on the one found in Alvarez et al. (2004). To quantify the illumination provided by a particular seismic survey I trace rays from the desired subsurface positions towards the surface. For each pair of specular rays, i.e. corresponding rays with the same angle respect to the horizon normal, I calculate their intersection points with the surface.

If for a specular ray i these two points are x_i and y_i I measure the set of distances $d(s_k, x_i)$ and $d(r_j, y_i)$, where s_k is a source and r_j is one of the receivers in the spread of s_k. The sum of all minimum distances is the illumination objective function:

$$O_I = \Sigma_i \min(d(s_k, x_i) + d(r_j, y_i)).$$

The best survey from the illumination point of view is the one that minimizes the value of O_I because in this case the specular rays are nearer, in the average, to a source-receiver pair than when O_I is greater.

Cost objective function

There are many costs associated to a seismic survey like drilling, receiver positioning, equipment rent, crew salaries, etc. To simplify, I assume that the cost of a seismic survey is proportional to the number of sources, although a more complete cost function can be used instead. The objective function is then defined as

$$O_C = N_s,$$

where N_s is the number of sources. The best survey from the cost point of view is the one that minimizes O_C.

Particle Swarm Optimization algorithm and Mesh Adaptive Direct Search algorithm

Particle Swarm Optimization (PSO) is a stochastic search procedure which uses a group of points that explores the solution space at different velocities (Eberhart and Kennedy, 1995). Mesh Adaptive Direct Search (MADS) is an optimization algorithm which explores locally an objective function (Audet and J. E. Dennis, 2006) using polling around a point. The idea behind the combination of PSO and MADS algorithms is to be able to search locally with MADS and at the same time, escape from local minima using PSO (Isebor et al., 2014).

Examples

To test the survey design bi-objective optimization a synthetic velocity model was created. Figure 1 left shows part of this model. The model is 10km wide and 2.5km deep. It has a curved reflector in the right that sweeps from 0° to 90° . This curved reflector is the region of interest that I want to illuminate.

I traced specular rays from points in the region of interest every 50m towards the top of the model. At each point 121 equally spaced rays were traced from −60° to 60° respect to the reflector normal at that point. The minimum separation Δr was set equal to 10m. The following table shows the limits of the survey parameters.

	Shot position (Km)	Live stations (Δg units)	Δg (Δr units)	Δs (Δg units)
Min	0	1	1	1
Max	10	100	10	5

I obtained the Pareto Front shown in Figure 1 right after the PSO-MADS bi-objective optimization algorithm was run with the described parameters. Each plus sign represents a survey with objective values O_I and O_C . The circles are the points that compose the Pareto Front. It can be observed the trade-off between illumination and survey cost along them.

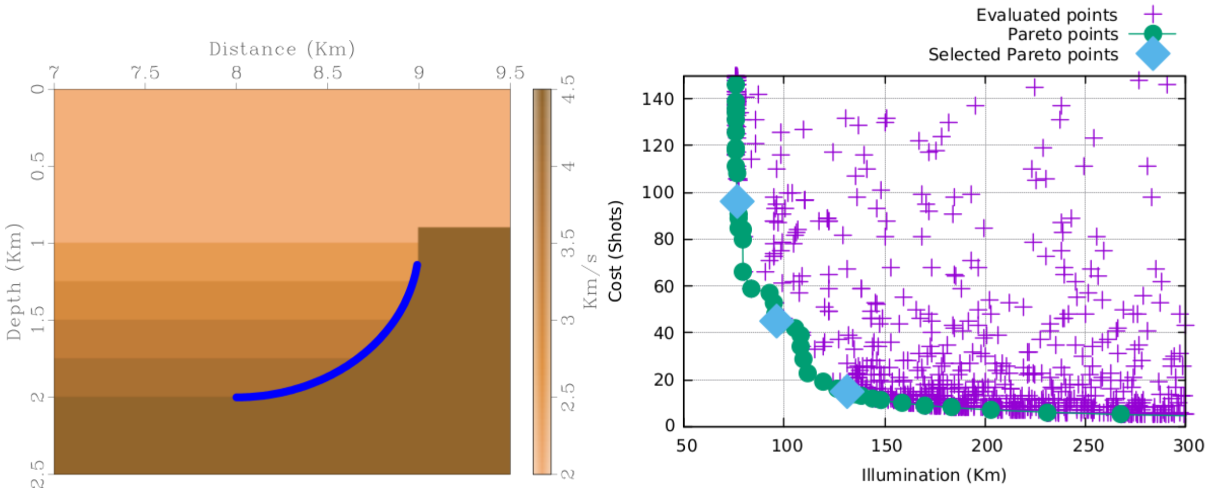

FIG. 1. Left: Velocity model with the region of interest is highlighted. Right: Pareto Front obtained from the bi-objective optimization.

I selected three of the surveys located at three different sections of the Pareto Front, shown as diamonds in Figure 1 right, to analyze the seismic image of the region of interest after a prestack depth migration is performed to data obtained using them. The following table exhibits the characteristics of each one of the selected surveys, named S1, S2 and S3, respectively. Survey S1 has 15 shots, S2 has 45 and S3 has 96.

Name	Shot zone (m)	Live stations	Δg (m)	Δs (m)
S1	6125 − 9085	1 − 100	50	200
S2	5495 − 9985	1 − 100	50	100
S3	4665 − 9455	1 − 100	50	50

Figure 2 shows the results after RTM prestack depth migration around the region of interest. The level of detail that I can get from this region is good in all surveys.

As a reference I also performed two more surveys. The first one is a usual survey with sources and receivers only above the target with 100 shots every 20m and 200 receivers per shot also every 20m in a split spread configuration. The other was a complete survey that covers all the horizontal model extension with receivers and sources spaced every 10m. Figure 3 displays the results of the prestack depth migration using these surveys. The usual survey shows less definition in the region of interest than the three surveys obtained by optimization. Also, the complete survey does not show more detail than the optimized ones.

Conclusions

I proposed an approach to seismic survey design that uses bi-optimization of two very important objectives: illumination and cost. Previous survey design optimization schemes were mainly focused in optimizing the illumination of subsurface targets or some other measure of the imaging quality.

As illumination and survey cost are contradictory objectives, the bi-optimization approach does not provide a unique answer but a set of surveys called Pareto Front that shows the trade-off between objectives. This offers insight into the interdependence of objectives that could be used not only as a design tool but as a decision tool.

The technique was tested with a synthetic example. Some surveys obtained by bioptimization were used to generate seismic data and compare their migrated images with a the image obtained by a more traditional design. The results are promising because a good image was achieved with a better cost.

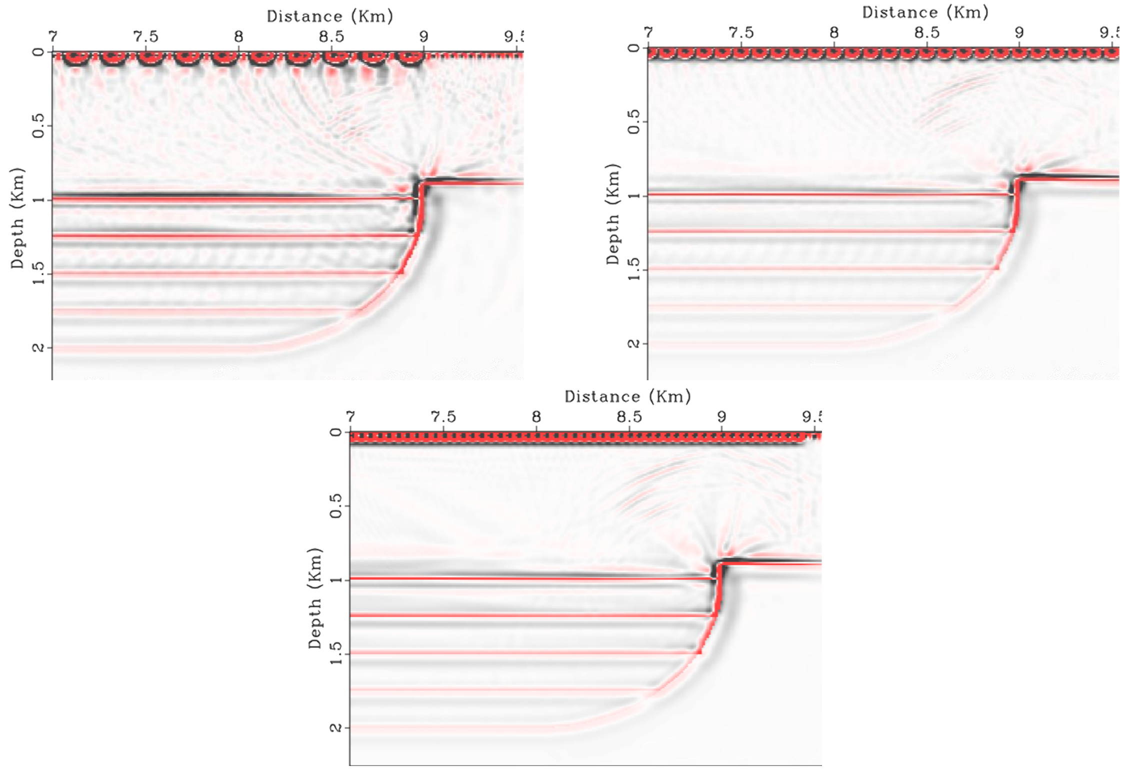

FIG. 2. RTM migrations of the selected surveys of Figure 1 right. Above are S1 with 15 shots and S2 with 45 shots. Below is S3 with 96 shots.

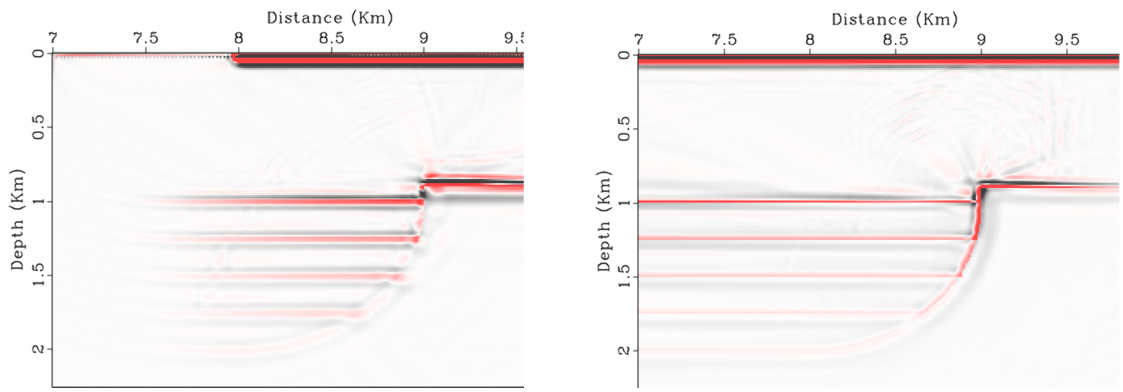

FIG. 3. RTM migrations from a usual survey (100 shots) and the complete survey (1000 shots).

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