# Bi-objective optimization for seismic survey design

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## ABSTRACT

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. I tested the optimization using a synthetic model and compared the final migrated seismic images. The results show good quality imaging and better cost.


## 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. In Djikpesse et al. (2012) a Bayesian optimization methodology for designing surveys that minimize the uncertainty of the model parameters is developed. Mohammad Hosseini Dokht et al. (2013) used a genetic algorithm to optimize a survey design in the southwest of Iran. Coles et al. (2015) describes an optimal survey design method to improve the big data applications of the seismic data.

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.

In the first part of this report the survey design bi-objective optimization methodology will be explained. In the second, this methodology will be applied to a synthetic example.

## 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, $\Delta r$, and allow receiver space $\Delta g$ to be an integer multiple of $\Delta r$, that is, only $\Delta r, 2\Delta r, \ldots, N\Delta r$, where the maximum receiver spacing, $N$, is also set by the user. In the same way, the source spacing $\Delta s$ 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.

As an example, if I set $\Delta r = 20m$, I can describe a split spread survey with receivers located every $\Delta g = 2\Delta r = 40m$, shots between $1005m$ and $6485m$ every $\Delta s = 4\Delta g = 160m$, the shortest source-receiver offset equal to $3\Delta g = 120m$ and the largest equal to $68\Delta g = 2720m$ with the following parametrization:

| Shot positions (m) | Live stations ($\Delta g$ units) | $\Delta g$ ($\Delta r$ units) | $\Delta s$ ($\Delta g$ units) |
|---|---|---|---|
| 1005-6487 | 3-68 | 2 | 4 |

### 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 $s_k$. Then I look for the minimum sum of the distances

$$S_i \quad = \quad \min(d(s_k, x_i) + d(r_j, y_i)). \tag{1}$$

This minimum sum says how far is the seismic survey from being able to record this pair of specular rays. The sum of all distances $S_i$ is the illumination objective function:

$$O_I \quad = \quad \sum_i \min(d(s_k, x_i) + d(r_j, y_i)). \tag{2}$$

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

$$O_C \quad = \quad N_s, \tag{3}$$

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

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). The velocity of each particle in the group is dictated by a procedure that imitates the social interplay of groups of animals. Each particle $\mathbf{x}_i$ in iteration $i$ advances using the following expressions:

$$\mathbf{x}_{i+1} \quad = \quad \mathbf{x}_i + \mathbf{v}_i \Delta t, \tag{4}$$
$$\mathbf{v}_{i+1} \quad = \quad a\mathbf{v}_i + b_1 D_{i+1}(\mathbf{x}_i - \mathbf{y}_i) + b_2 E_{i+1}(\mathbf{x}_i - \hat{\mathbf{y}}_i). \tag{5}$$

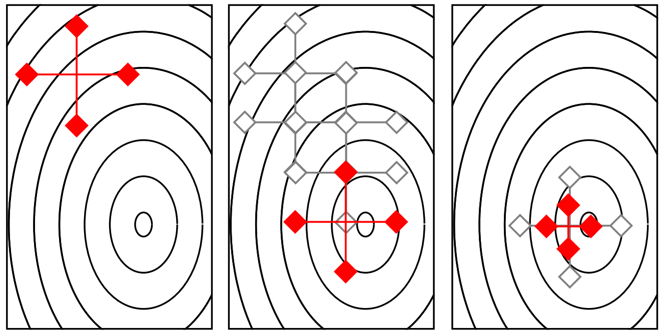

FIG. 1. MADS algorithm performing the polling around a point. The concentric ellipses are level curves of the objective function surface.

In the first expression $\mathbf{v}_i$ is the velocity and $\Delta t$ the time step that usually is set to $1$. In the second expression each term on the right hand side represents three different forces. The first one is the inertial term that tries to maintain the velocity equal to the previous one using coefficient $a$. The second term is the cognitive term that tries to be near the previous particle best position $\mathbf{y}_i$. The third term is the social term that tries to be attracted to the current best position, $\hat{\mathbf{y}}_i$, in the vicinity of $\mathbf{x}_i$. I use a random vicinity for each particle. The diagonal matrices $D_{i+1}$ and $E_{i+1}$ have random values between $0$ and $1$ and help to obtain variety in the velocities. Clerc (1999) recommends using $a = 0.729$ and $b_1 = b_2 = 1.494$.

## Mesh Adaptive Direct Search algorithm

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. Polling begins by choosing a set of points or stencil around the initial point as Figure 1 shows. If one of the stencil points has a better objective function value than the current point and the other stencil points, the current point takes the value of this stencil point. The central part in Figure 1 shows how the central point advances by taking the place of the stencil point with the lowest objective funtion value. If none of the stencil points has a better objective function value that the current point, the size of the stencil is decreased as the right part in Figure 1 illustrates.

MADS also changes the directions of the stencil points from one iteration to the next choosing the new one from an asymptotically dense set of directions (Audet and J. E. Dennis, 2006).

## PSO-MADS algorithm

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. The algorithm is the following (Isebor et al., 2014):

**Algorithm 1** PSO-MADS

Generate initial particle swarm $S$<br>
**for** k = 1 to maxiter **do**<br>
    **repeat**<br>
        success = PSO($S$)<br>
    **until** success is false<br>
    **repeat**<br>
        success = MADS(best point in $S$)<br>
    **until** success is false<br>
**end for**

In the pseudocode the function PSO updates the swarm $S$ and returns true if the swarm has points with better objective function values. The function MADS is applied to the best point found by PSO and returns true if a better point is found.

## Pareto Front

The Pareto Front is defined in terms of dominance. If there are two surveys $x^{(1)}$ and $x^{(2)}$ with illumination and cost values $(O_I^{(1)}, O_C^{(1)})$ and $(O_I^{(2)}, O_C^{(2)})$, respectively, it is said that $x^{(1)}$ dominates $x^{(2)}$ if $O_I^{(1)} \leq O_I^{(2)}$, $C_I^{(1)} \leq C_I^{(2)}$ and at least one of these relationships is a strict inequality (Isebor et al., 2014).

To illustrate this point consider Figure 2 left. This figure shows part of the dominance area of survey $x^{(4)}$. It can be seen from the dominance definition that $x^{(4)}$ dominates all surveys inside this area, including their boundaries. The right part of the same figure shows the combined dominance areas of all surveys. The Pareto Front is defined as the set of surveys that are not dominated by any other survey. From the figure this set is composed by $x^{(1)}$, $x^{(4)}$ and $x^{(6)}$.

Each point $x$ in the Pareto Front have some merit because the points that have better illumination than $x$ do not have better cost and the ones that have better cost, do not have

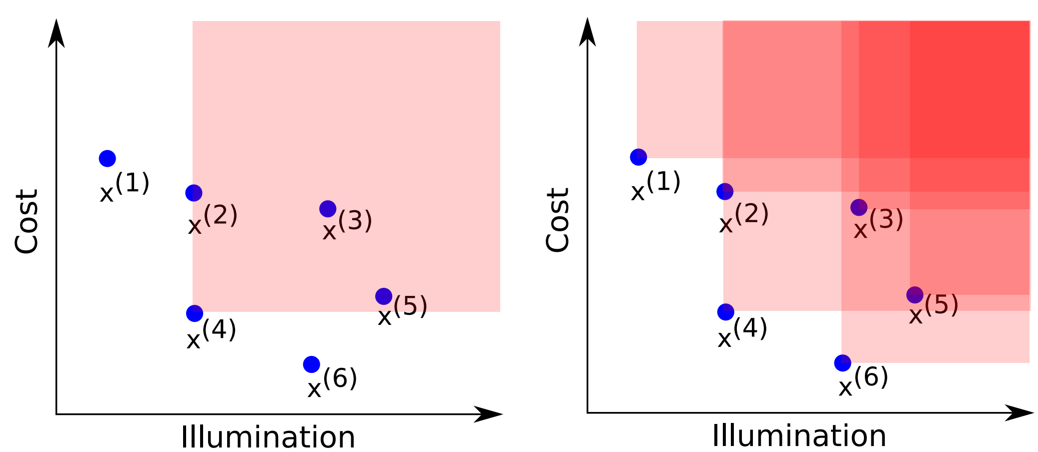


FIG. 2. Dominance relationship. Left: Dominance zone of $x^{(4)}$. Right: Combined dominances. Non dominated points $x^{(1)}$, $x^{(4)}$ and $x^{(6)}$ belong to the Pareto Front.

better illumination. For example, consider $x^{(6)}$ in Figure 2. Surveys $x^{(1)}$, $x^{(2)}$ and $x^{(4)}$ have better illumination than $x^{(6)}$, but none of them have better cost. In this way, the Pareto Front exposes the trade-off between illumination and cost that gives more insight to the survey designer.

On the other hand, if $x$ does not belong to the Pareto Front, by the definition of dominance it can not be better than its dominant survey in any sense, and should be considered a suboptimal survey.

### Bi-objective optimization

In order to optimize the two objective functions $O_I$ and $O_C$, I minimize a convex combination of them:

$$\min(w_1 O_I + w_2 O_C), \tag{6}$$

for several values of $w_1$ and $w_2$ using the PSO-MADS algorithm. This procedure generates surveys along the Pareto Front in most cases. A more sophisticated strategy is to use the approach proposed in Audet et al. (2008).

## RESULTS

To test the survey design bi-objective optimization a synthetic velocity model was created. Figure 3 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 used a Huygens wavefront ray tracer (Sava and Fomel, 1998) to trace 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

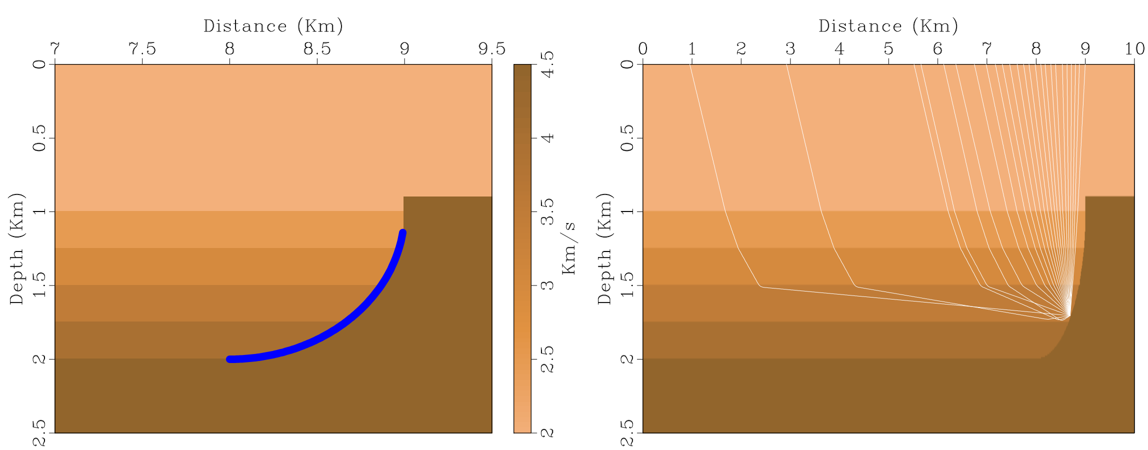


FIG. 3. Left: Velocity model with the region of interest is highlighted. Right: Specular rays traced from the region of interest.

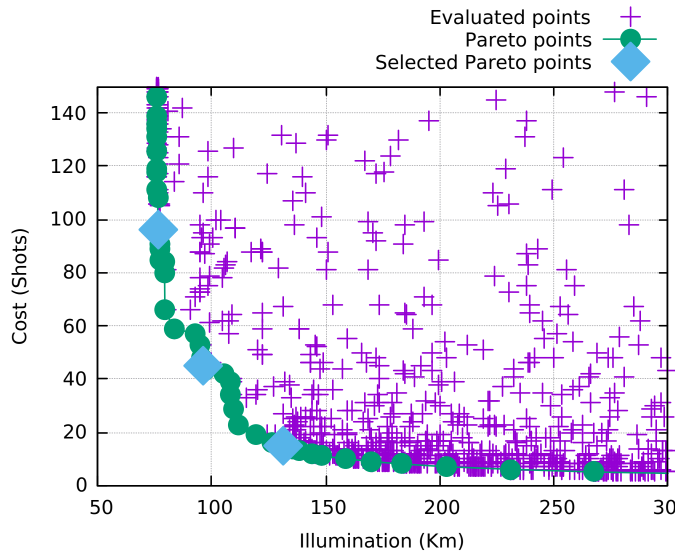


FIG. 4. Pareto Front obtained from the bi-objective optimization.

point. Figure 3 right displays some of the specular rays traced from a point in the region of interest.

The minimum separation $\Delta r$ was set equal to $10m$. The following table shows the limits of the survey parameters.

| | Shot position (Km) | Live stations ($\Delta g$ units) | $\Delta g$ ($\Delta r$ units) | $\Delta s$ ($\Delta g$ units) |
|---|---|---|---|---|
| Min | $0$ | $1$ | $1$ | $1$ |
| Max | $10$ | $100$ | $10$ | $5$ |

From the table the separation between receivers $\Delta g$ varies between $10m$ and $100m$ while the source separation $\Delta s$ varies between $10m$ and $500m$.

I obtained the Pareto Front shown in Figure 4 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.

I selected three of the surveys located at three different sections of the Pareto Front, shown as diamonds in Figure 4, 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 $96$. The Figure 5 shows graphically the shot zone of each survey.

| Name | Shot zone (m) | Live stations | $\Delta g$ (m) | $\Delta s$ (m) |
|---|---|---|---|---|
| S1 | $6125 - 9085$ | $1 - 100$ | 50 | 200 |
| S2 | $5495 - 9985$ | $1 - 100$ | 50 | 100 |
| S3 | $4665 - 9455$ | $1 - 100$ | 50 | 50 |

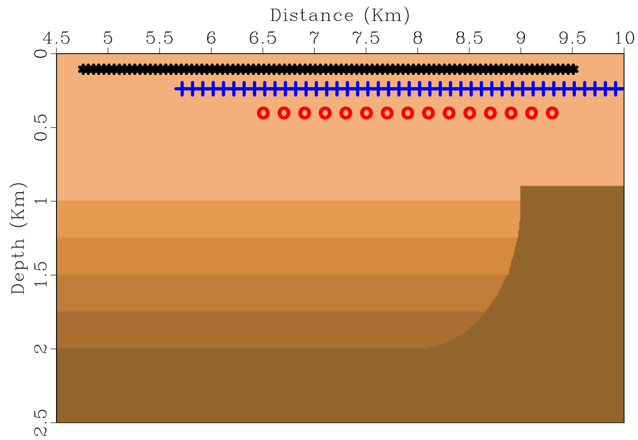


FIG. 5. Source locations of the selected surveys. S1 is marked by circles, S2 by plus signs and S3 by asterisks.

The shot modelling was made with a four order in space and second order in time optimized finite difference scheme with hybrid one-way absorbing boundary condition. The prestack migration was performed using a reverse time migration algorithm. Figure 6 shows the results after 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 $20$m in a split spread configuration. The other was a complete survey that covers all the horizontal model extension with receivers and sources spaced every $10$m. Figure 7 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.

## DISCUSSION

The chosen surveys from the Pareto Front produced a good image of the region of interest because they located sources and receivers where the actual specular rays emerge at the surface. The optimization algorithm reached this kind of design automatically.

With knowledge of the region of interest a person could have proposed similar designs with similar results in this simple case. However, in more complex cases, the use of the computational power and the optimization should provide survey designs that are more difficult to obtain using usual design rules.

The usual survey used in the comparison was proposed having in mind only the CMP assumption by only allowing sources and receivers above the region of interest. Although this assumption does not hold here, it is in the very core of the usual design rules.

In this work I used two relatively simple objective functions but it is possible to include a more realistic cost function and more advanced imaging quality measures.

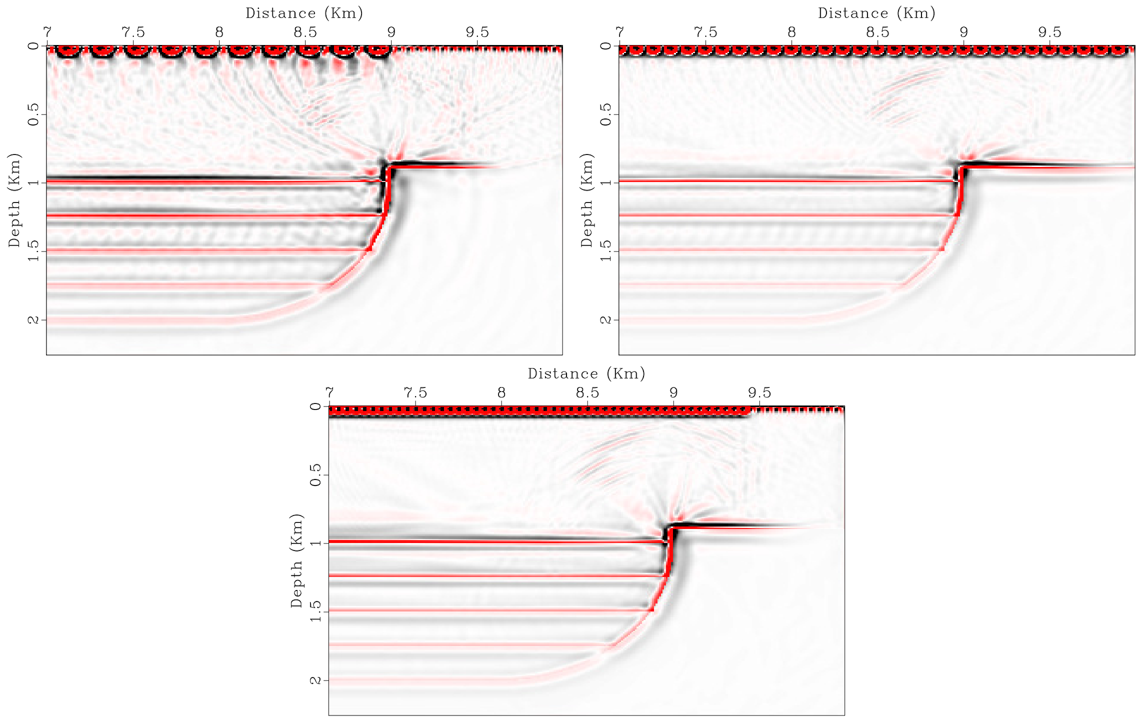


FIG. 6. RTM migrations of the selected surveys of Figure 4. Above are S1 with $15$ shots and S2 with $45$ shots. Below is S3 with $96$ shots.

As the objective was deep and there were no concerns about spatial aliasing the optimized surveys showed very long spacings between sources and between receivers. As already mentioned, a more complete objective function should take care of that in more realistic cases.

## 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 while leaving the economic part free or as an optimization constraint.

The method uses an algorithm that not only does local optimizations but also searches the complete survey space. This algorithm can also handle real and integer quantities and this is very useful because survey design has both types of variables.

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 bi-optimization 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

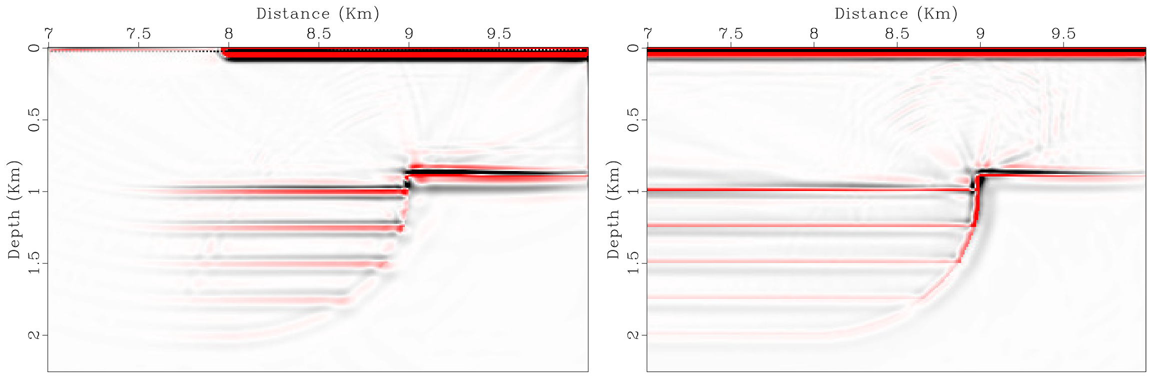


FIG. 7. RTM migrations from a usual survey ($100$ shots) and the complete survey ($1000$ shots).

image was achieved with a better cost.

## FUTURE WORK

I propose some ideas for improving this work:

1. Test the technique with more complex synthetic examples that will show how the bi-optimization obtains designs more difficult to reach using usual design rules.
2. Test more complete objective functions. For example for the illumination part I could use rose diagrams (Cao et al., 2012), point spread functions (Routh et al., 2005) or image resolution measures (Richard L. Gibson and Tzimeas, 2002).
3. Besides aiming the design to obtain a good migrated image of the region of interest I could also try to predict the response of the survey to other processes like 5D interpolation or footprint noise suppression, for example.
4. Extend the technique to 3D models and to multicompoment data by trying to improve the response of the S-wave image too.
5. Propose a field experiment to test the optimized designs.

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