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.

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.

Illumination objective function

For each pair of specular rays I calculate their intersection points with the surface. If for a specular ray i these two points are x_i and y_i we 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 the minimum of all these distances is the illumination objective function:

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

Cost objective function

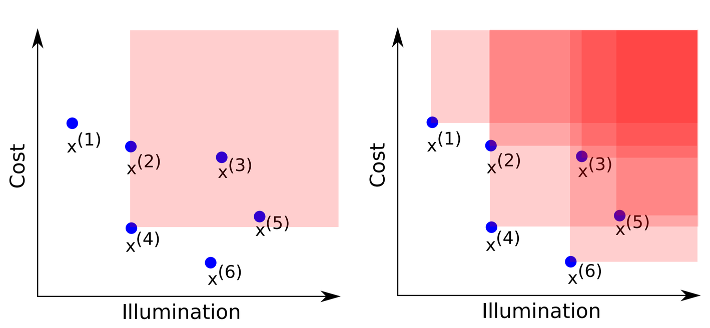
To simplify, I assume that the cost of a seismic survey is proportional to the number of sources, The objective function is then defined as

$$O_C = N_s$$

where N_s is the number of sources.

Pareto Front

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. The Pareto Front is defined as the set of surveys that are not dominated by any other survey.



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.

Particle Swarm Optimization

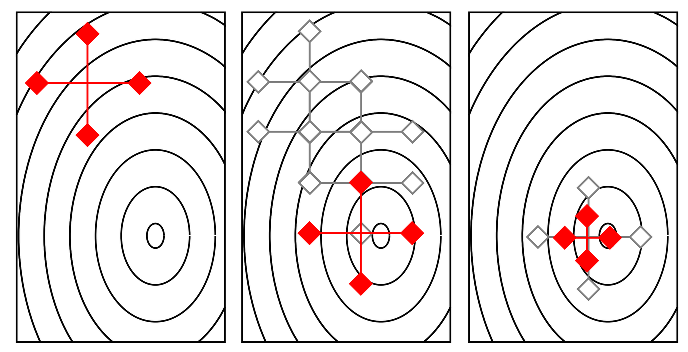
Particle Swarm Optimization (PSO) is a stochastic search procedure which uses a group of points that explores the solution space at different velocities. Each particle $\mathbf{x}_i$ in iteration i advances using the following expressions:

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

where $\mathbf{v}_i$ is the velocity of particle $\mathbf{x}_{i+i}$ and is determined by three terms: a governs the inertial term, b_i the cognitive term and b_2 the social term.

Mesh Adaptive Direct Search algorithm

Mesh Adaptive Direct Search (MADS) is an optimization algorithm which explores locally an objective function using polling around a point.



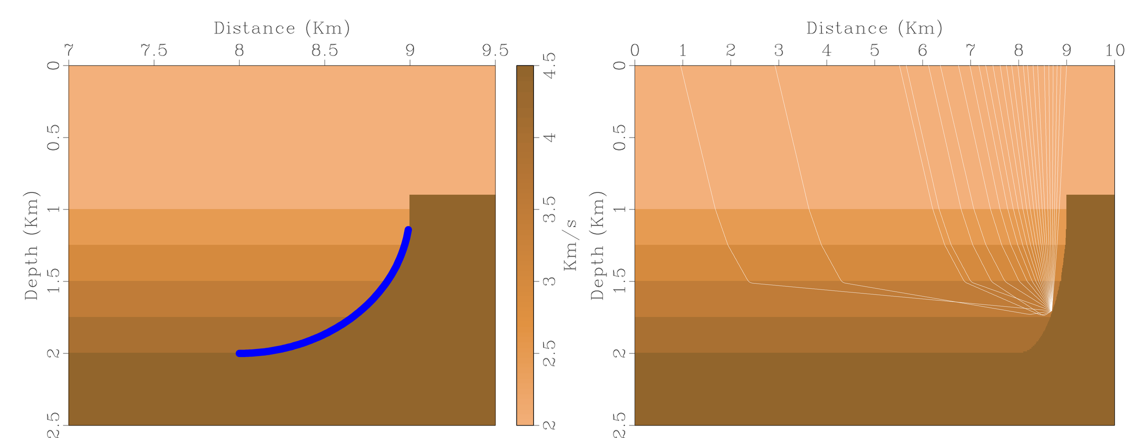
Bi-objective optimization

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

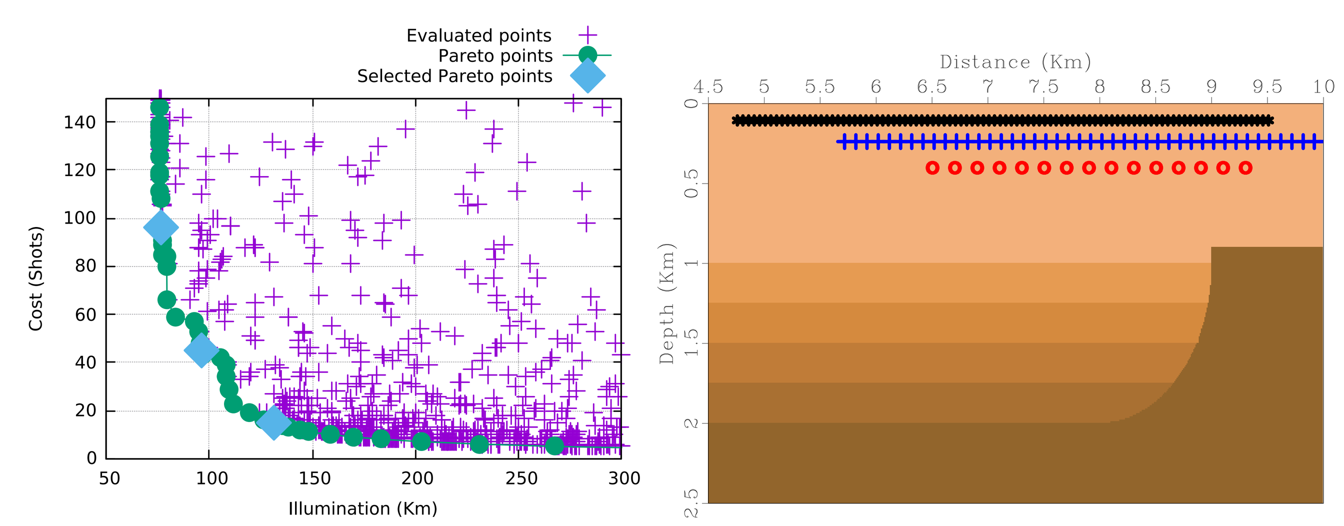
$$\min(w_1 O_I + w_2 O_C),$$

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.

Example



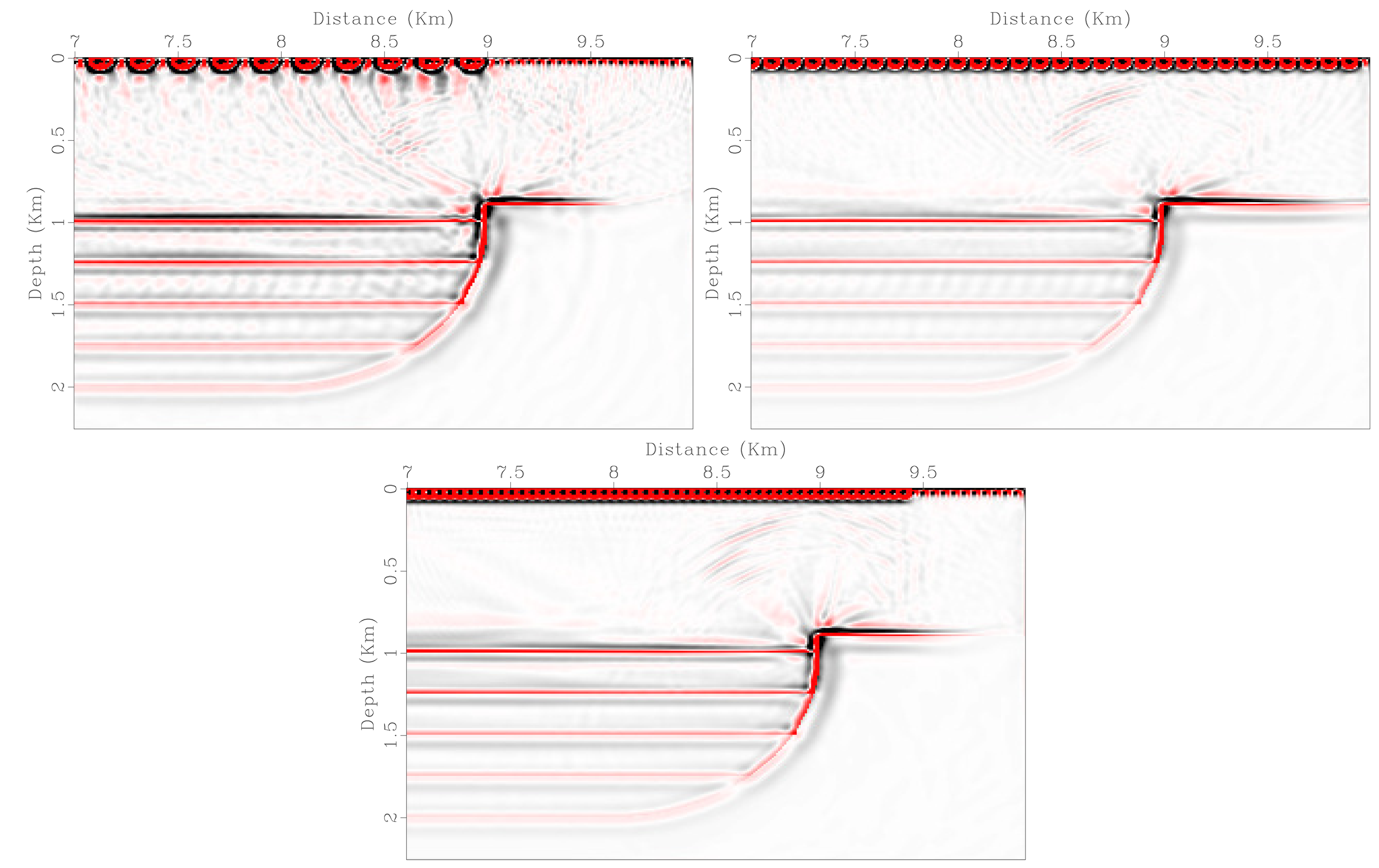
Left: Velocity model with the region of interest is highlighted.
Right: Specular rays traced from the region of interest.



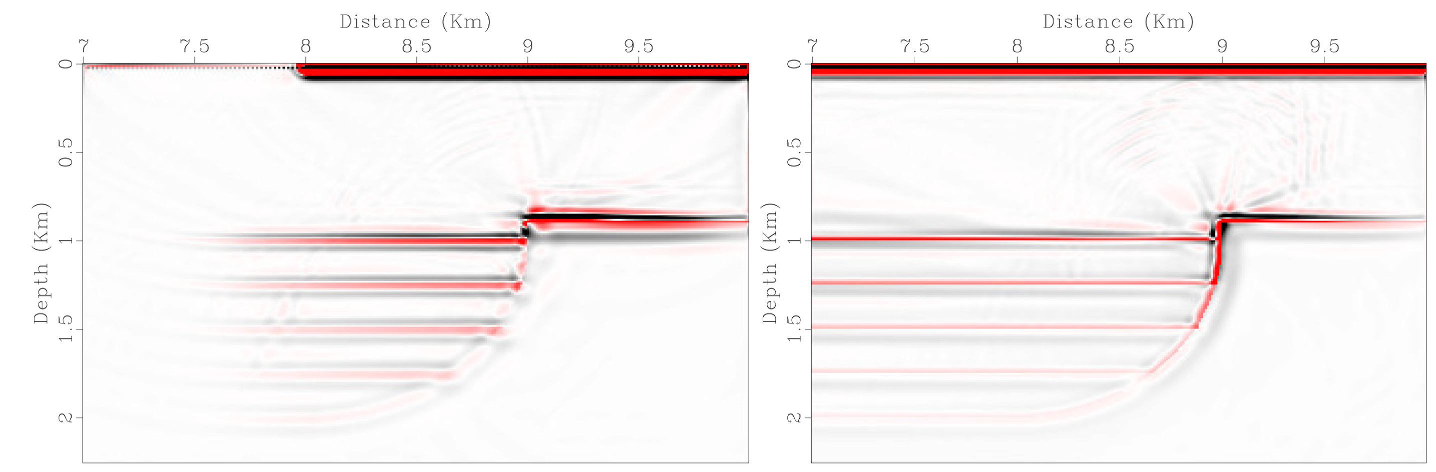
Left: Pareto Front obtained from the bi-objective optimization.
Right: Source locations of the selected surveys. S1 is marked by circles, S2 by plus signs and S3 by asterisks.

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

Parameters of surveys S1, S2 and S3.



RTM migrations of the selected surveys S1, S2 and S3. Above are S1 with 15 shots and S2 with 45 shots. Below is S3 with 96 shots.



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

Future 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, point spread functions or image resolution measures.
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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Bibliography

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