Fast Search Algorithms for Automatic Localization of Microseismic Events

Ulrich Zimmer*
Pinnacle – A Halliburton Service, Calgary, Canada
ulrich.zimmer@pinntech.com
and
Jeremy Jin
Pinnacle – A Halliburton Service, Calgary, Canada

Summary

Detecting and locating microseismic events automatically has become a very important tool in processing large datasets in seismically very active formations. Although some formations produce only a few hundred events during a typical hydraulic fracture treatment, many shale formations are very active resulting in thousands of locatable events for a single stage. Grid search methods have proven very fast and effective in locating microseismic events. For small 2-dimensional grids each grid point can be evaluated as a potential event location but these models are only appropriate for surveys with a single sensor array and relatively simple velocity models. More complex velocity structures and surveys with multiple sensor arrays require three-dimensional models with a very large number of individual grid points. To locate events within a reasonable timeframe, usually a few seconds, it is necessary to limit the grid search to a subset of data points. Algorithms like Artificial Bee-Colony (ABC), Simulated Annealing (SA) and Differential Evolution (DE) have proven in general very fast and effective in this type of problems. Each of these algorithms is best for certain types of data. Implementing different algorithms with different search strategies provides a lot of flexibility to optimize the automatic event localization resulting in reliable phase identification and faster processing times.

Introduction

Automatic processing using migration or refraction stack based methods is routinely applied to locate microseismic data as it does not require prior knowledge of the phase arrivals. The arrivals of P- and S-waves are provided as an output once the most likely event location is determined. In grid search methods each grid point represents a potential event location and its probability of being the event location is evaluated using the traveltimes to the sensors as stacking templates on the recordings. A full search of the grid space would require the evaluation of each individual grid point which is very time-consuming even in medium size grids. Since the location probability varies (at least to some degree) smoothly from grid point to grid point, other methods than the linear search can be employed. Although these methods have the potential to get stuck at the wrong grid point, this can be mitigated to some degree by the tuning of the method parameters to the individual dataset.

Theory and/or Method

Many methods exist to find the global minimum (or maximum) of an objective function in a grid space. The group of meta-heuristic algorithms starts out with a random group of grid points and derives new grid points to evaluate from the value of the objective function at these points. Once a specified criterion is met, the search is stopped and the point with the minimum (or maximum) function value is declared the solution (figure 1). The methods vary mainly in how the original grid points are chosen, how the new grid points are derived and when to stop the search. Simulated Annealing (SA) and especially Differential Evolution (DE) (Gharti et. Al., 2009) are algorithms that have received much attention more recently. Differential Evolution (DE) with its different search strategies appears to be well suited for the problem of finding the most likely event location in the shortest amount of time with a very high success rate. Especially in uni-modal problems, i.e. for distributions with only a single minimum (or maximum), the Differential Evolution algorithm outperforms other algorithms. For multi-modal benchmark distributions, i.e. distributions that have many local minima (or maxima), the new Artificial Bee Colony algorithm reportedly outperforms Differential Evolution algorithms (Li et al., 2010).

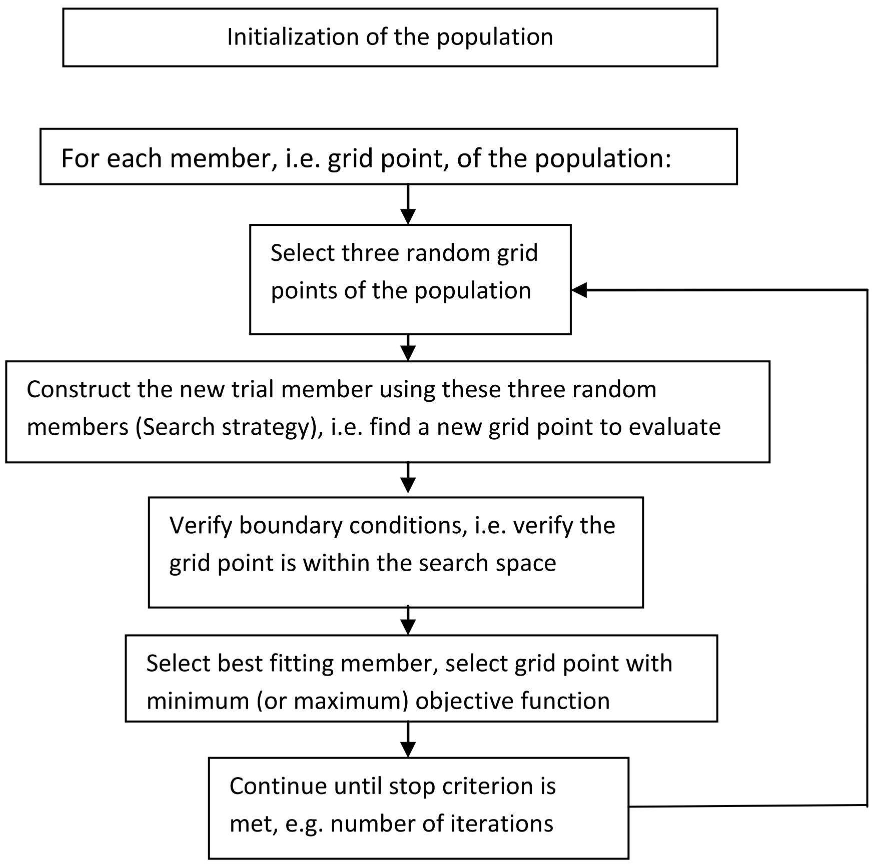

Figure 1: Differential Evolution (DE) search

Examples

Figure 2 shows slices through the three-dimensional grid space with each grid point assigned the value of the objective function, i.e. the probability that the event location is in (or close to) this grid point. On the left of Figure 2 the linear grid search evaluates every single grid point before choosing the most likely event location. In this case, this requires calculation on approx. 4 million grid points. The right side shows the same grid but different search space for a genetic algorithm like Differential Evolution. In this case much fewer grid points have to be evaluated before the correct solution is reached. This results in a very significant reduction of the search time.

Table 1 summarizes typical search times for a 4 million node grid space. These search times and the quality of results depends on the complexity of the objective function's distribution in the grid space. For seismic signals with a single clear P- and S-wave arrival the objective function is relatively simple having just one prominent maximum (Figure 2). For events with multiple arriving P- or S-signals or with signals that have a general low signal/noise-ratio the objective function will have multiple maxima of almost equal value (Figure 3 shows a basic example). In such cases, it is possible that a search algorithm that evaluates only a very small part of the overall grid space wrongly identifies a local maximum as the best solution. To avoid this, each method has certain parameters that can be adjusted to the specific problem to ensure fast convergence to the correct solution. So far the Artificial Bees Colony (ABC) and Differential Evolution (DE) algorithms have been proven to be suited for the type of objective function used in this example for automatic event location. Other forms of the objective function can be defined but the general problem of multiple maxima in the grid space will likely be independent from its specific definition. Another advantage of algorithms like ABC and DE is that their time requirements do not scale linearly upwards with the number of grid points. Where doubling the number of grid points doubles the time requirements for a linear search the increase in search time for algorithms like ABC or DE is much less.

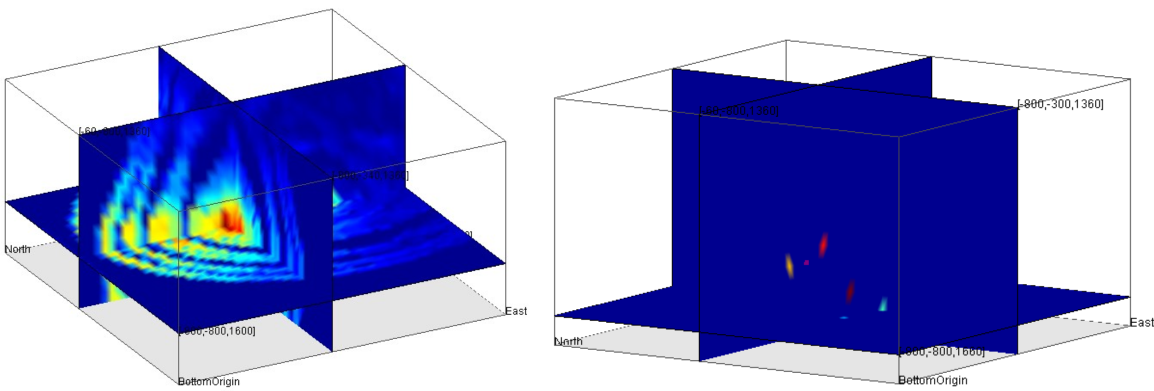

Figure 2: Different search spaces for linear grid search (left), Differential Evolution (right)

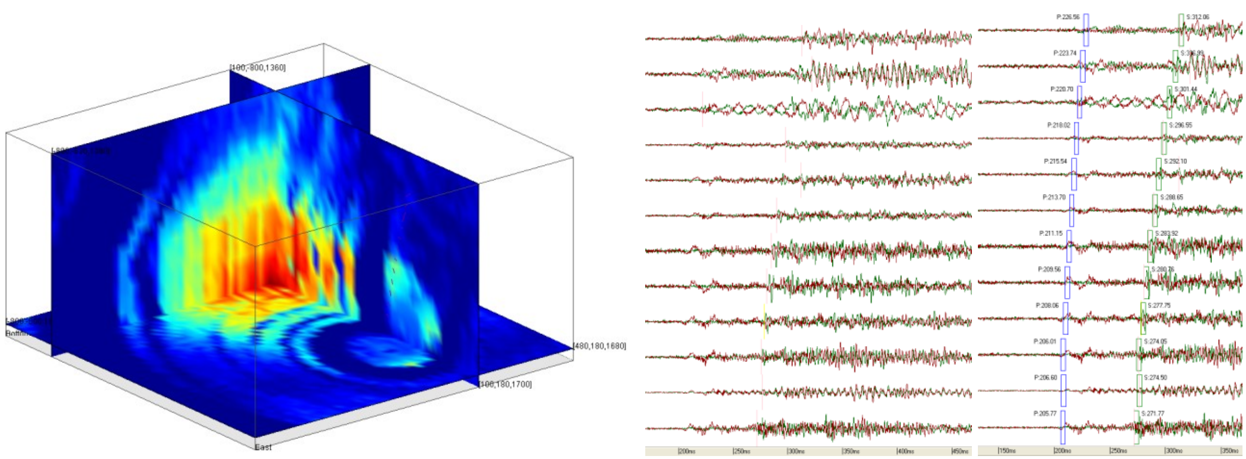

Figure 3: Complex search space for multiple phase arrivals (left), corresponding waveforms (right)

In addition to the internal parameters, some methods can be even further adapted to the specific problem to be solved. In Differential Evolution for example the *search strategy*, i.e. the way the new trial grid point is determined, is an integral part of its implementation (Feoktistov, 2006). These strategies can be random, directed, local or a combination of those. For objective functions that have a single clear maximum, directed search strategies can point the solution quickly to the global maximum. For distributions with numerous local maxima the directed search has a higher probability to converge to the wrong maxima, where random searches are more likely to find the global maximum within a given number of iterations.

Table 1: Effectiveness of different search algorithms on a 4 million node grid

Search Algorithm	Run time (s)	Comments
Linear Grid Search	326.4	Always finds the global maximum
Artificial Bee Colony	2.0	Works generally well
Simulated Annealing	1.4	Did not get the correct result
Differential Evolution	1.1	Works generally well

Conclusions

Although linear grid searches provide reliable results when searching for a global optimum on a grid space, these methods are often too slow for larger grid spaces. Meta-heuristic search algorithms like Differential Evolution and Artificial Bee Colony work generally well for automatic event location and provide a lot of internal flexibility to adjust to a specific dataset. Given the typical objective function for searches in four-dimensional spaces (3 spatial, one temporal dimension) these algorithms are very well suited to provide fast and stable solutions.

Acknowledgements

We like to thank Prof. Dervis Karaboga for providing the implementation of his Artificial Bee Colony (ABC) algorithm.

References

Feoktistov,V.L Optimization and its Applications (Volume 5):Differential Evolution – In Search of Solutions, Springer 2006

Gharti, H.N., Oye, V., Roth, M., Kuehn, D., 2010: Automated microearthquake localization using envelope stacking and robust global optimization, Geophysics Vol.75, No.4, p MA27-MA46.

Li, H., Liu, K., Li X., 2010, A Comparative Study of Artificial Bee Colony, Bees Algorithms and Differential Evolution on Numerical Benchmark Problems, Communications in Computer and Information Science, Volume **107**, Part 5, p.198-207.