Evolutionary Algorithms for MRS Single and Joint Inversion

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SUMMARY

As inversion of magnetic resonance data requires a resistivity model, joint application of MRS with VES or TEM is inevitable. Moreover, joint inversion, e.g. by common block models, can improve resolution and decrease ambiguity. In contrast to derivative-based methods, global optimization can provide a variety of models that reflect uncertainty. We apply different evolutionary algorithms (e.g. GA, PSO) to data sets from the North Sea island of Borkum.

Computations with the open Python library *inspyred* show that the individual algorithms have different properties concerning convergence and diversity. Joint inversion of MRS and VES is achieved by a non-dominated sorting genetic algorithm. The Pareto rank of the achieved models shows how well the two data can be fitted

Key words: MRS, joint inversion, global optimization, evolutionary algorithms.

INTRODUCTION

Inversion of geophysical data is prone to ambiguity, i.e. a variety of models is able to fit the data within target misfit. Joint inversion of different data sets can reduce the ambiguity if the underlying geometry is identical. As the inversion of Magnetic Resonance Sounding (MRS) data requires a resistivity model to calculate the magnetic fields, a joint application with any resistivity method is favourable, either transient electromagnetics (TEM) (Vouillamoz et al., 2012; Behroozmand et al., 2012) or vertical electrical soundings (VES) (Günther & Müller-Petke, 2012; Akca et al., 2014).
In inversion, mostly least-squares (LS) algorithms are used to minimize the objective function. The result of this local minimization scheme depends on the starting model, accordingly any computed uncertainty describes the local behaviour of the objective function but cannot tell about the global spread of possible solutions. Global optimization algorithms search through the parameter space randomly and are able to create a set of solutions fitting the data sufficiently, thus displaying equivalence without being trapped in a local minimum. Evolutionary algorithms (EA) have long been used for geophysical tasks, recently Akca et al. (2014) used Genetic Algorithms (GA) for 1D MRS/VES joint inversion.
Questions are:

- Which algorithms are suited and fast?
- How to select proper parameters?
- Are results and convergence stable?
- How to trade-off convergence and diversity?
- What can EA tell us what LS cannot?
- How to join different methods?
- Can EA and LS methods be combined?

We present results from three joint MRS+VES soundings from the North Sea island of Borkum (Günther & Müller-Petke, 2012).

METHODS

In a QT inversion scheme, the complete (gated) time series of all pulse moments are simultaneously inverted (Günther & Müller-Petke, 2012). Unknowns in 1D MRS inversion are thickness d, water content θ and relaxation time T_2^* of the layers. If VES is jointly inverted, additionally resistivity ρ becomes part of the model and the data vector is extended by the apparent resistivity. All data are weighted by their uncertainties to balance the different physical units and to contain a normal Gaussian misfit distribution.
We use the free and open-source Python library inspyred for parameter estimation. It brings along the following algorithms:

- Genetic Algorithm (GA)
- Evolution Strategy (ES)
- Differential Evolution Algorithm (DEA)
- Estimation of Distribution Algorithm (EDA)
- Simulated Annealing (SA)
- Particle Swarm Optimization (PSO)
- Ant Colony System (ACS)

An object-oriented implementation allows clear scripts and multiple processors can be used for speed-up. By a flexible design classical or own methods can be combined. A typical workflow would be:

Create initial population using GENERATOR
Evaluate initial population using EVALUATOR
while TERMINATOR is not True:

- Choose parents via SELECTOR
- Generate offspring using VARIATOR
- Evaluate offspring using EVALUATOR
- Replace individuals using REPLACER
- Migrate individuals using MIGRATOR
- Archive individuals using ARCHIVER
- Call OBSERVER for export/statistics

The EVALUATOR computes the fitness of the members using the objective function. For a typical GA we use a VARIATOR that is a combination of blended crossover and Gaussian mutation, a tournament type SELECTOR, and a generational REPLACER.
For joint inversion of different data sets one could combine the two individual objective functions. Alternatively, we compute the Pareto rank, i.e. all non-dominating members obtain rank 1 as used in the NSGA-II algorithm presented by Deb et al. (2000). See Figure 1 for the flowchart.

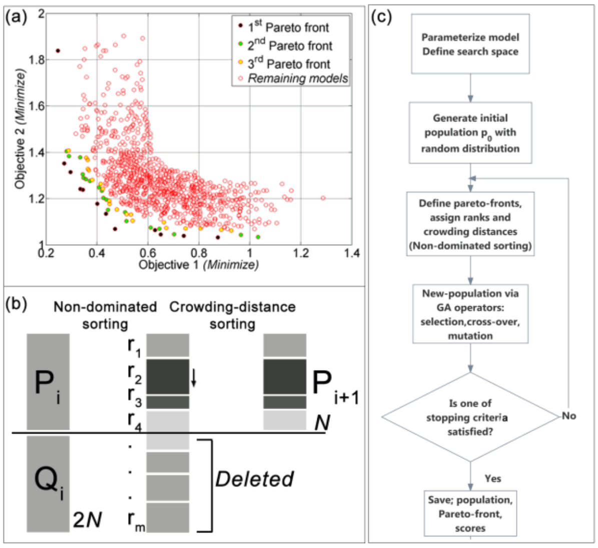

Figure 1. NSGA-II non-dominating sorting procedure and flowchart for multi-objective optimization.

The algorithms were applied to various data sets from the North Sea Island of Borkum (Günther & Müller-Petke, 2012) Subsurface consists mainly of fluviatile fine sands with interbedded silt layers.

SINGLE INVERSION

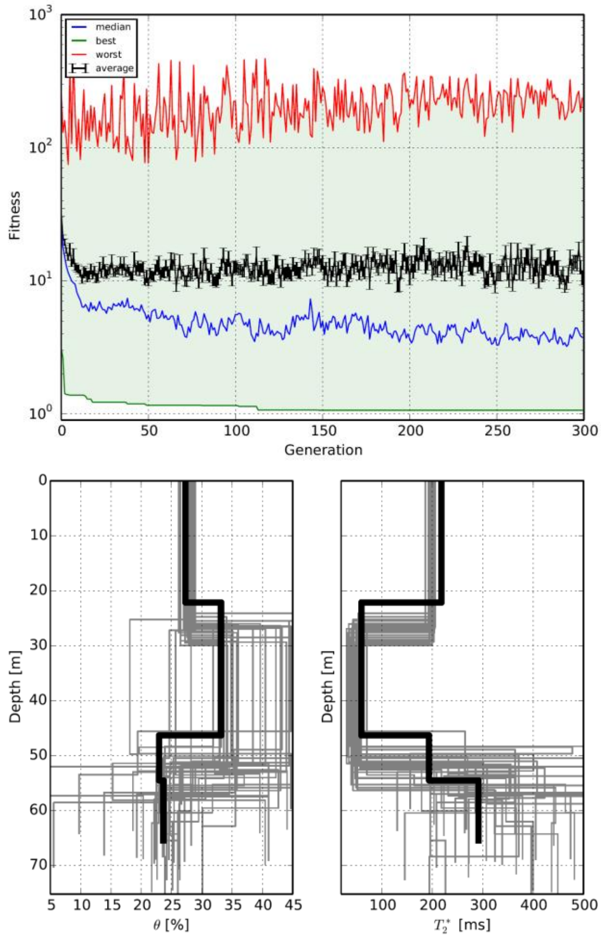

Figure 2. Results and convergence of GA for data CL2.

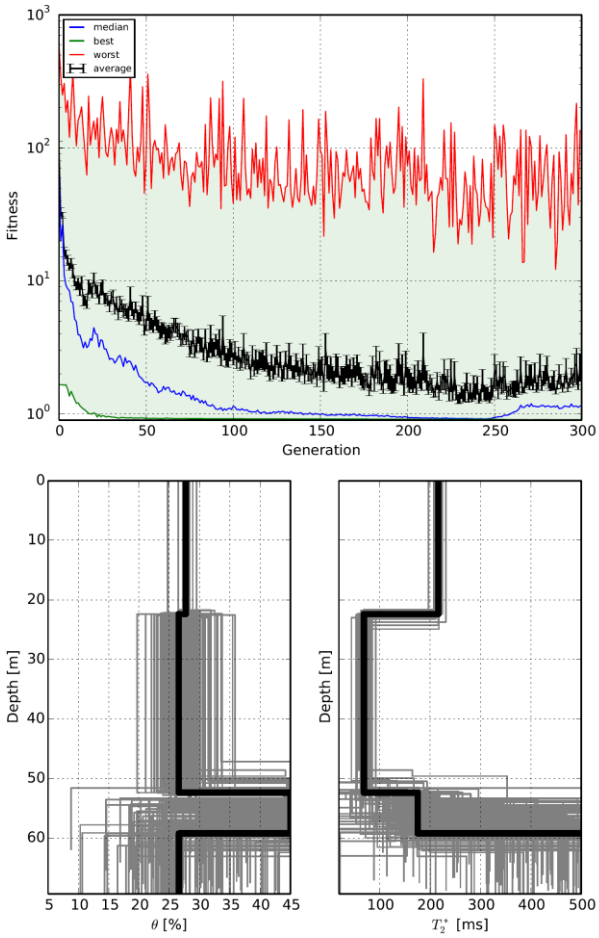

Figure 3. Results and convergence of PSO for data CL2.

A population of 500 was used for all EA algorithms, amongst which GA and PSO proved superior. Figures 2 and 3 show the convergence statistics and the resulting models (models with chi-square values below 2). GA converges very slowly but retains a wide spread of models. PSO is converging much faster to the target value of 1. The majority of the swarm members fits the data to an acceptable degree, but the diversity of model types is lost. Hence the PSO uncertainty is rather a local measure (as for LS), whereas GA seems to better illustrate global model equivalency.

JOINT INVERSION

Figure 4 illustrates the evolution of the population. The two objective functions for the 100 best individuals are plotted using colours to indicate the generation number. Whereas the distribution is rather smooth at the beginning, after about 100 generations the cloud starts forming an L-shaped structure. Even after 300 generations (stopping criterion), the curve is not fully converged, especially for the VES data. The individuals form almost a Pareto front which is roughly a corner but not perfectly. Further iterations are needed to decide whether the double corner can be overcome or not.

In contrast to the individual inversion there is clear evidence for the silt layer know from a borehole in about 30m depth. The ambiguity of the models is reduced by the coupling of the two models by their thickness.

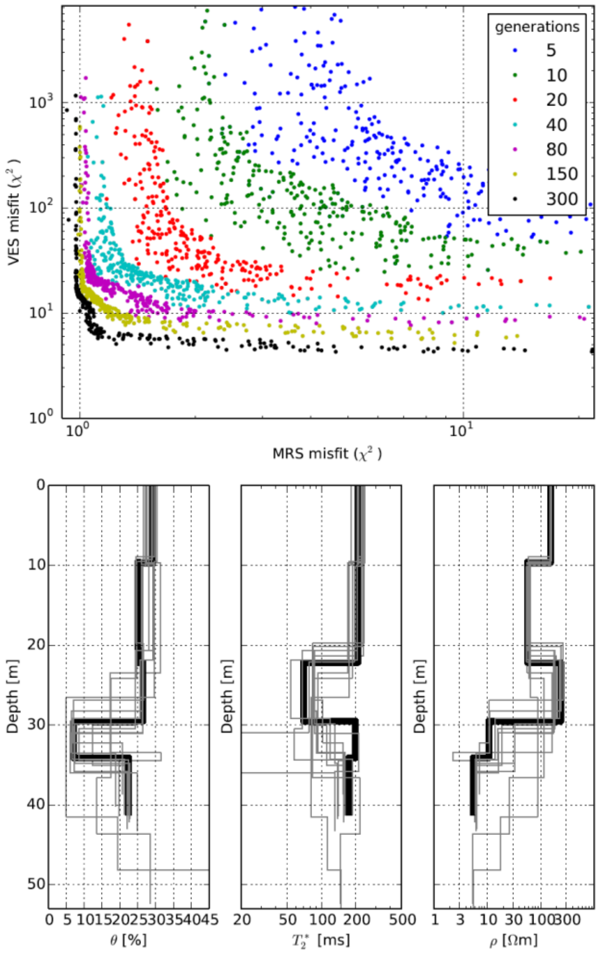

Figure 4. Resulting models and convergence of the NSGA-II algorithm for sounding CL2.

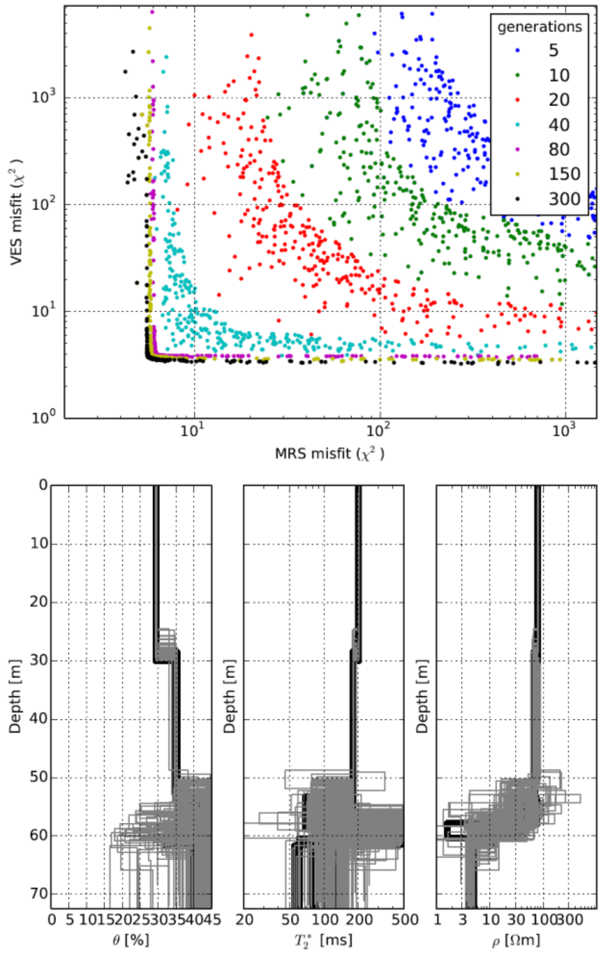

Figure 5. Resulting models and convergence of the NSGA-II algorithm for sounding OD33.

The results of a second sounding in the dune area (OD33) is shown in Figure 5. Compared to CL2, the convergence is faster and already after 80 iterations an almost perfect L shape is reached. Obviously the two data sets are fitting together. The overall chi-square values are about 4 for both methods, but cannot be improved by further iterations.
In the models there is none with the thin silt layer as detected by the least-squares inversion. The resistivity clearly shows the freshwater-saltwater interface, but above there is not much variation in the sandy aquifers. Uncertainty is strongly increased in deeper regions of lower resolution.

A third sounding was made in the flooding area at the boundary of the fresh-water lens (sounding SKD). At this position there might be 3D effects from the rough terrain and the laterally changing near-surface conditions. Furthermore, the corresponding VES sounding was made in a distance of a few hundred meters so that a coincidence of the subsurface model is not ensured.
Inversion convergence is similar to the CL2, characterized by a slow development. Even after 300 iterations we cannot observe convergence although the curve becomes very smooth. Both methods reach chi-squared values of about 2, but no model is able to fit both data sets similarly well. There are two distinct corners, one close to the minimum MRS misfit and one close to the minimum VES misfit. Obviously the two data sets do not describe the same subsurface. The imperfect shape of the curve gives hints to inconsistency.

Nevertheless, the resulting layer models show the expected behaviour: a brackish water layer on top of a silt layer, below fresher water before the freshwater-saltwater interface is reached. There are significant equivalences for both water content and relaxation time of the lower layers, probably due to lowered resolution as a result of the good conductors channelling the B fields.

CONCLUSIONS

Evolutionary algorithms can give valuable insight into the subsurface. They are able to generate a set of different models and thus a measure of equivalency. Among the algorithms provided by the library *inspyred*, GA and PSO proved to be fast and robust, but exhibit different behaviour. PSO is very fast, but the injective movement of the swarm leads to reduced diversity in the models. On the other hand, GA converges much slower, but keeps different model types. Equivalences shown by GA is definitely more global than by PSO.
Joint inversion of MRS and VES can be achieved by the NSGA-II algorithm using Pareto rank optimization. The shape of the curve and the convergence reveals information about consistency between the two methods. Whereas a clear L shape denotes that geometry is matching, several corners hint to multi-dimensional effects.

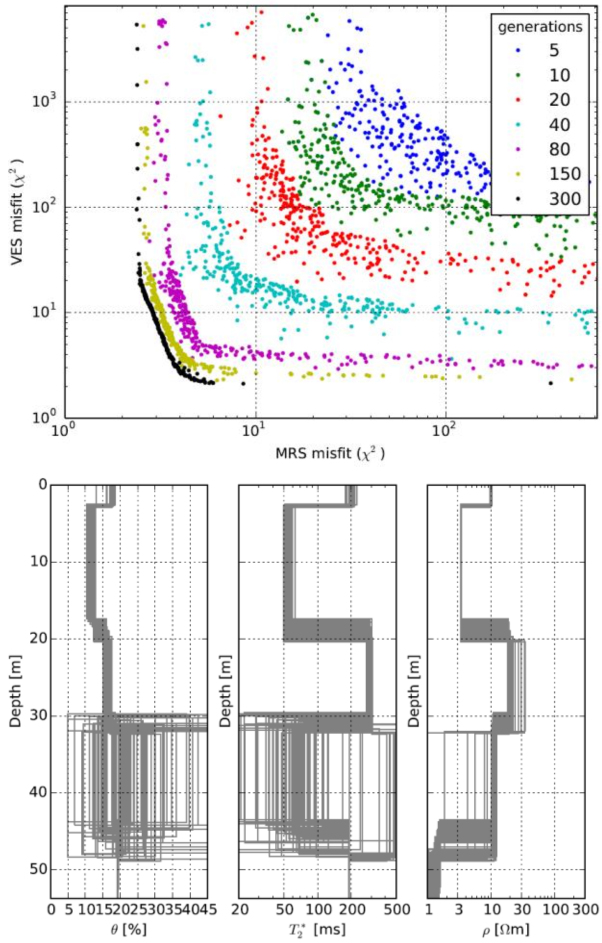

Figure 6. Resulting models and convergence of the NSGA-II algorithm for sounding SKD.

As two-dimensional inversion of MRS data has been already demonstrated (Dlugosch et al., 2014), evolutionary algorithms might also contribute to single or joint inversion of MRT and ERT data. However, to keep the number of parameters and thus runtime slow, structure-based models as used by Attwa et al. (2014) would be the method of choice. Alternatively, structural coupling between models with fixed parameterization could be used.

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REFERENCES

Akca, I., Günther, T., Müller-Petke, M., Basokur, A. T. & Yaramanci, U. (2014): Joint parameter estimation from magnetic resonance and vertical electric soundings using a multi-objective genetic algorithm. *Geophysical Prospecting*, 62 (2), 364-376.

Attwa, M., Akca, I., Basokur, A. T. & Günther, T. (2014): Structure-based geoelectrical models derived from genetic algorithms: A case study for hydrogeological investigations along Elbe River coastal area, Germany. *Journal of Applied Geophysics*, 103, 57-70.

Behroozmand, A., Auken, E., Fiandaca, G., and Christiansen, A. V. (2012): Improvement in MRS parameter estimation by joint and laterally constrained inversion of MRS and TEM data, *Geophysics*, 77, WB191–WB200.

Deb K., Agrawal S., Pratap A. and Meyerivan T. (2000). A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II, Tech. Rep. 2000001, Kanpur Genetic Algorithms Lab. (KanGAL), Kanpur, India.

Dlugosch, R., Günther, T., Müller-Petke, M. & Yaramanci, U. (2014): Two-dimensional distribution of relaxation time and water content from surface NMR. *Near Surface Geophysics*, 12, 231-241.

Günther, T., & Müller-Petke, M. (2012): Hydraulic properties at the North Sea island of Borkum derived from joint inversion of magnetic resonance and electrical resistivity soundings. *Hydrol. Earth Syst. Sci.*, 16 (9), 3279-3291.

Vouillamoz, J., Hoareau, J., Grammare, M., Caron, D., Nandagiri, L. & Legchenko, A. (2012): Quantifying aquifer properties and freshwater resource in coastal barriers: a hydrogeophysical approach applied at Sasihithlu (Karnataka state, India), *Hydrol. Earth Syst. Sci.*, 16 (9), 4387–4400.