

# Interactive Inversion in Geological Applications

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## Abstract

We compare IGA to traditional numerical inversion on a geological application. We show that ‘a priori’ information and expert knowledge can overcome lack of accurate data and help convergence towards a satisfactory solution.

## Introduction

A standard goal in geology is to unravel the geological history of a region. This is often crucial to understanding its potential economic value. In general, this is equivalent to determining the initial conditions that generated a certain process, from its final configuration. Many similar problems are encountered in applied mathematics and engineering, under the name of inversion.

Geoscientists have to face another hurdle in their work. Both spatial and temporal distributions of data are very sparse. Consequently, two quite sophisticated processing stages are needed in standard geological studies: spatial and temporal data interpolation and extrapolation, and inversion. The hardware used for such processing is the geoscientist’s brain; the software being his accumulated knowledge, training, experience and scientific opinions.

This implies a high degree of subjectivity in the analysis. Such subjectivity requires two, somewhat contradictory components, imagination and assumptions. Imagination introduces the ability to conceive and explore far-from-obvious solutions. Assumptions, on the other hand, may suppress unexplored but valid solutions.

Nevertheless, this subjectivity is necessary. Fully automated systems for data analysis and Artificial Intelligence approaches have been attempted with only limited success. In modern high-tech geological exploration, it is still the geoscientist, not the tool, who discovers mineral/oil deposits.

Fast computers have allowed the development of quite sophisticated forward modelling of geological processes. However, such forward models are used in a traditional trial-and-error fashion, can be both time consuming, and strongly influenced by the geoscientist’s expectations and *a priori* knowledge.

Here, we present a first step in the development of a system for interactive inversion of geological processes. Its main aim is:

1. to allow a more systematic application of geological forward modelling codes;
2. to provide a formal role for relevant experience in the forward modelling process
3. to suggest valid solutions falling outside the range of original expectation

## Method

Inversion attempts to estimate the value of a set of parameters that, when used as initial conditions in a particular forward modelling code, reproduce target data within a certain error. Such error is normally measured numerically. There are problems for which such numerical estimation is not possible, or not reliable. Typical examples can be found in artistic applications. Determining whether the graphical output of a program is pleasing or a sequence of musical notes is enjoyable, can not be achieved by numerical estimation, rather there is the need of a human judgement.

Similar problems are found in geology. Often we do not have numerical measures that are representative enough to establish the appropriateness of a geological model. As a typical example, it is often possible to build models that can fit measured data, but at times such models are not geological feasible or do not have any resemblance to ‘real’ geology. Although it is often easy for an experienced analyst to discard such models, it is very hard to construct an algorithm to do so. Research on the topic is under way in different institutes but very little progress has been made so far.

The approach we propose is based on the use of an Interactive Genetic Algorithm (IGA) (Takagi, H.,1998) . A genetic algorithm is used to perform a global search in the solution space. We refer the reader to Goldberg () for a description of Genetic Algorithms and to Boschetti et al. (1996) for the specific GA implementation used in this work. The quality of the solutions produced by the GA (i.e., the equivalent of the numerical misfit in traditional inversion) is input by an expert geoscientist who judges and ranks the solutions according to his/her experience and *a priori* knowledge.

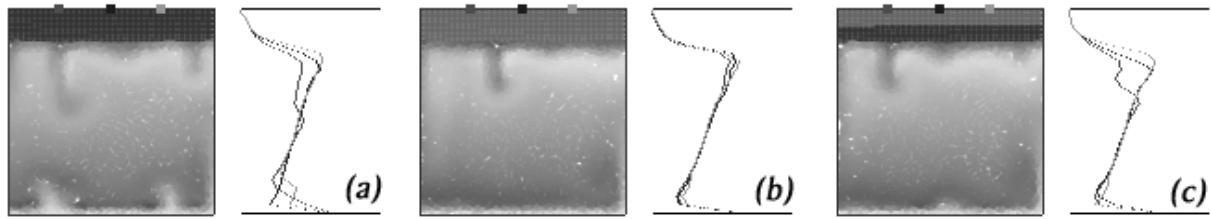


Figure 1. The final frames from the preferred simulation for the “expert” (a), “non-expert” (b), and for the fully automated run (c). The vertical profiles at three sample points are temperatures used to gauge the fitness of the solution by the users together with the overall pattern of the temperature field (shading). The numerical inversion was restricted to matching the central profile. The dark layers at the top of each box are the compositionally distinct materials representing the Earth’s crust.

In the specific test described in this paper, the solutions are represented by animations of thermal convection in the Earth mantle. The user is provided with a single image representing a 2-D geological vertical section (See figure 2, top). The purpose of the experiment is to deduce the parameters (e.g. material properties) of the simulation that produce this geological section after the system has evolved for a specified time. The user is presented with a number of animations (see Figure 1). Each animation has been generated by the GA, through its standard stochastic behaviour, coupled with the physical forward model. The user then views the movies and ranks them according to: 1) how close the final configuration is to the target section, 2) how ‘geologically feasible’ the overall animation (i.e., the geological evolution) is, 3) his/her general experience and knowledge of the area under analysis. After the ranking is done, the GA starts its usual process and generates a new set of movies for the next evaluation. The process keeps on until the user is satisfied with the result, i.e. a movie that looks geologically reasonable and a final result close to the target image.

The technique has two major advantages compared to purely numerical evaluation: 1) it would be very difficult to provide a numerical evaluation of the similarity between the target and the produced final images. Notice that what is important is not the pixel by pixel similarity, but the overall geological similarity (for example, two images could be very similar pixel by pixel but contain a different number of major faults or layers, which would make them completely different from a geological perspective. The opposite is also true: two images could be very different pixel by pixel but contain similar geological ‘structures’), 2) It would be very hard to evaluate numerically whether the animation makes geological sense, i.e. whether it simulates a geologically reasonable dynamic evolution.

The technique has also major advantages compared to purely human driven ‘trial and error’ forward modelling; 1) the internal GA process can speed up convergence to a satisfactory solution; 2) the GA performs a global search, thus avoiding being trapped

in local minima (in this case, the psychological equivalent of a numerical local minimum is being blinkered by expectations, without considering alternative scenarios). The code should be able to ‘suggest’ to the analyst valid solutions that may be different from his/her expectations and *a priori* knowledge.

### The geological simulation

A crucial parameter for the understanding of deep crust-mantle heat convection is the geotherm, i.e., the (increasing) temperature profile in the earth as a function of depth. The continental geotherm determines whether magmas can be generated, and the extent to which rocks undergo geochemical processes. The geotherm can be measured directly only in the shallowest few km’s of the crust, and indirectly at greater depth through mineralogical methods when small samples are ejected in volcanic eruptions.

This is a classical coupled heat flow problem and the forward model is, in principle, very simple to solve using a finite element fluid flow code. However, in the practical case, it is extremely difficult to know the parameters of the forward model (radiogenic heat production of deep crust and mantle, thermal conductivity of the lower crustal rocks, Rayleigh number of the mantle, and the global partitioning of heat flow between oceans and continents). A summary of the geological context of the simulations can be found at <http://www.ned.dem.csiro.au/research/solidMech/Geodynamics/>.

These uncertainties lead to an inverse problem where the parameters to be determined include the physical properties of the crust and mantle. As already mentioned, in geology, such problems are usually tackled by repeated forward modelling and a good deal of intuition based upon simple one-dimensional scaling laws.

From the inversion point of view, this is a useful test problem. The fit to the geotherm for any given forward problem is quantitative so that, theoretically, a genuine automatic inversion can be performed. There is also the possibility that the additional information available in the evolution of the movie in two dimen-

sions will allow an expert operator to speed the inversion, as well as discard model of little geological meaning. Finally, in the practical situation, only the uppermost part of the geotherm can be measured with the remaining constraints coming from assumptions based on the physical processes involved in the system. The extent to which these assumptions are helpful in constraining the inversion can be tested explicitly.

### Experimental Evaluation

Three tests have been run. The first test consisted of a traditional numerical optimisation. The misfit used was the squared error between the ‘measured’ temperature profile and the one generated as final result of the animation. In the second test an experienced geoscientist (the author of the forward modelling code) performed a human driven inversion, taking into account both the similarity between the temperature profiles (but no numerical misfit) and the geological ‘quality’ of the animations. In the third test an unexperienced user (a geoscientist with no specific experience in mantle circulation) substituted the experienced one. Figure 2 shows an iteration of the human-driven inversion just prior to the ranking process. The image in the top left is the target end point for the animations, and the movie in the bottom left is the highest ranked solution from the previous iteration which is required for the non-quantitative inversion to ensure consistency of ranking.

The final frames of each of the solutions from the three experiments are shown above in Figure 1. Frame (a) was guided by the expert in convection, (b) was guided by the non-expert, and (c) was obtained by the automatic inversion based on the misfit to the profile (shown alongside each image). The lid thicknesses are all identical although the component layers differ. The convective vigour is also well matched by each of the runs. The other parameters are expressed by more subtle variations in the form of the profile (e.g. in curvature near the surface) and have not been well constrained by the purely visual inversion or the fully automatic one. This is, in part, due to the transient nature of the target problem in which the longer-timescale effects are not given time to develop. This results in an effective elimination of many of the free parameters. The misfit to the central profile was the only information used by the automatic inversion. The expert user also made use of the information contained in the form of the profiles although without the benefit of the numerical misfit.

### Discussion

A number of interesting observations can be drawn from this experiment:

1) The results from the interactive (human driven) inversion were comparable, both in terms of quality and speed, to the purely numerical one. This is a very important result for geological applications, in which reliable data are rare and often sparse. For this specific application, as stated above, reliable temperature data can be obtained only close to the Earth’s surface, and measurements at depth can only be extrapolated from other data. In this test, the numerical inversion was given an unrealistic advantage in assuming error free temperature measurements along the entire profile. The ability of the geoscientist to operate without such data looks very promising.

2) The two geoscientists used different strategies in the inversion, clearly influenced by their expertise. Solutions characterised by specific features judged of particular relevance to the problem were selected even if their global similarity to the target image was relatively poor. Basically, the users had performed a sort of mental eigen-vector decomposition, with the selection of what were considered the crucial directions of the search. This process is completely transparent in the traditional GA run, in which only data misfit, without extra information is used.

The two geoscientists were also using their knowledge of the inner mechanics of GA inversion in their choices, paying attention to leave certain ‘good’ features in the GA population even if belonging to low quality individuals. This is again impossible for a GA, that is ‘unaware’ of its own mechanics.

These two strategies carry both advantages and disadvantages. The disadvantage lies in directing the GA run too strongly, with the risk of disrupting its main advantage - the global search.

The advantages are the possibility of speeding up the search and using *a priori* information. Also, there may be the option of interactively controlling some GA parameters, including the population’s size and rate of mutation, depending of the convergence speed and variability in the population. This offers a completely new avenue to explore.

3) While numerical inversion is sensitive only to the temperature profile, human driven inversion is sensitive particularly to geological structures and to dynamic evolution. Both are modelled as colour images in the animation. Specific choices of the colours will allow the discrimination of certain features at the expenses of others. This confirms previous results on IGA: the selection of a proper visualisation and user interface becomes a crucial part of the inverse problem.

### Conclusion

The problem at hand was a relatively simple one, and should be considered as a sort of proof of concept.

Other interesting aspects of the inversion, like being able to prevent instability in the numerical inversion by interactively disregarding unstable solutions, could not be tested. This will be one of the subject of future experiments.

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### Inversion Geology Movies

The figure displays a grid of 15 panels, each representing a different frame of an inversion geology simulation. Each panel consists of two parts: a grayscale image of a geological cross-section on the left and a corresponding line profile on the right. The panels are arranged in three rows and five columns. The top-left panel shows the target image. The bottom-left panel shows the best result from the previous iteration. The other panels show intermediate results. Each panel includes a 'Rank' dropdown menu set to 'Not Ranked Yet'. A 'Submit Query' button is located at the bottom center.

Frame: 30 Timestep: 00297	Frame: 30 Timestep: 00297	Frame: 41 Timestep: 00296	Frame: 42 Timestep: 00298	Frame: 30 Timestep: 00291
Frame: 42 Timestep: 00298	Frame: 41 Timestep: 00297	Frame: 31 Timestep: 00295	Frame: 37 Timestep: 00276	Frame: 32 Timestep: 00300
Frame: 72 Timestep: 00299				

Submit Query

Figure 2. Snapshot of interactive ranking process at the end of one iteration, immediately prior to the user ranking the images. The target image is shown top-left and the best result from the previous iteration (required to provide consistency in ranking between generations) is shown at the bottom left. The entire evolution of the simulation is available to the user by clicking on the images — this allows the user to include information from subtle clues in the time-evolving behaviour which may not be apparent in the profiles of the end-state.