GEOPHYSICS, VOL. 66, NO. 4 (JULY-AUGUST 2001); P. 1226–1234, 9 FIGS.

Interactive inversion in geosciences

F. Boschetti and L. Moresi*

ABSTRACT

Inversion algorithms numerically evaluate the mismatch between model and data to guide the search for minima in parameter spaces. In an alternative approach, the numerical evaluation of data misfit can be replaced by subjectively judging the solution's quality. This widens the class of problems that can be treated within the framework of formal inverse theory—in particular, various geophysical/geological/geodynamic applications in which structural similarity between model and data determines the quality of the fit. In this situation, prior knowledge, experience, and even personal intuition are crucial. This approach also provides a simple way to include such expertise in more traditional numeric applications, e.g., to treat ambiguous problems and disregard geologically unfeasible solutions from the inverse search.

INTRODUCTION

Inversion is an important tool when interpreting geophysical data. It attempts to reconstruct rock property distributions from measurements of their physical responses. This is achieved by a more-or-less structured search into a parameter (rock properties) space using physical forward modeling.

In the early stages of development, such searches were performed manually by a human operator adjusting some guess about the geological setting. The search would proceed in a trial-and-error fashion, matching measured data and reconstructing a reasonable geological model. This method is often called forward modeling. Much research in the last two decades has been concentrated on automating this sort of process using sophisticated inversion procedures. Automation appears to eliminate most of the subjective judgment involved in repeated forward modeling by removing operator input.

In reality, however, the subjectivity is not removed; it is simply hidden because the presence of a priori (purely subjective) assumptions is still crucial for the successful outcome of automatic inversion procedures—although in a much more subtle way. The inherent nonuniqueness underlying all geophysical inverse problems requires additional information to select a single solution among the ensemble of infinite rock-property distributions able to fit measured data. Such information may be provided in the form of (1) a specific starting model for the inverse run, (2) a specific parameterization restricting the search to predetermined geometrical shapes, or (3) an extra mathematical requirement for the solution, as maximum smoothness or sharp boundaries, at times chosen more for mathematical convenience than for geologic reason. Since such assumptions are often hidden deep in the inverse algorithm. The black-box use of such tools leaves the average user unaware of the precise nature of these assumptions and hence unable to judge whether the assumptions themselves are suited to a particular case.

In recent years fast computers have allowed the development of quite sophisticated forward modeling of geodynamic processes. Plate tectonics, faulting and folding, mantle convection, and fluid flow could, in principle, be treated in an inverse process, much as in traditional seismic/potential field problems. The potential of such applications would be tremendous, given that, broadly speaking, reconstructing initial geological configurations from their geological responses (determining the stress field that generated a certain folding pattern, for example) is very much what geology is about and is an implicit inverse problem tackled daily in every geologist's brain.

At present, geodynamic modeling is almost exclusively confined to the forward modeling stage. The physical intuition of the modeller is very important in this field because the data are usually extremely sparse and may only provide constraints on some integral property of the system. The quality of a solution is often judged according to its resemblance to patterns seen in the field, to the fact that it does not contradict basic geological principles, or simply to the modeler's expectations. Fit to data can be used as a further criterion when available, but this is rarely possible in a formal mathematical way. Even when extensive data are available, the choice of a proper cost function is not straightforward. A way to measure geological similarity and equivalence of geological structures is still very much a research topic.

Manuscript received by the Editor December 6, 1999; revised manuscript received December 5, 2000.
*CSIRO, Division of Exploration and Mining, 39 Fairway, P.O. Box 437, Nedlands, Western Australia 6009, Australia. E-mail: fabio@ned.dem.csiro.au; louis@ned.dem.csiro.au.

For the time being, at least, subjectivity, knowledge, experience, and intuition still play a major role in geophysical/geological modeling. The implementation of 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.

Recently, research in artificial intelligence (AI) developed systems to support artistic creativity (Takagi, 1998a,b). These systems have been used, for example, in graphic design and music composition. The systems take advantage of fast computation to generate a suite of images or music sequences. Then, an artist looks at the different images or listens to pieces of music and ranks them according to personal tastes. An inversion strategy takes into account such judgment in a formal mathematical way to generate a new set of images/music sequences, iteratively converging toward the artist's tastes/inspiration.

We propose extending such techniques to geophysical/geological applications in which subjective judgment is necessary either to discriminate between ambiguous solutions or to evaluate geological models in the absence of sufficient constraints. In doing so we present the first step in the development of a system for interactive inversion of geophysical/geological processes. The system offers three main useful features: (1) it allows a more systematic application of forward modeling codes as an advance on the time-consuming trial-and-error approach, (2) it provides a formal role for relevant geological experience and knowledge in inversion that often is extremely difficult to translate into mathematically rigorous constraints, and (3) it may suggest valid solutions falling outside the range of original expectation by facilitating a brainstorm process between the geoscientist and the inversion procedure.

We show the potential of the technique in two applications. In the first case we compare the interactive, subjectively driven inversion to a traditional numerical inversion for a synthetic mantle convection problem. The results show that user experience may in some cases replace lack of accurate data. Such comparison with purely numeric inversion, to our knowledge, has never been presented in the interactive inversion literature. In a second test we use the interactive inversion to seek a particular configuration of extensional features in a mechanical model of a stretched, brittle layer. This example comes from a practical case: the search for a specific yet mechanically consistent initial condition for a basin-inversion simulation. The interactive inversion proved very capable in this instance, whereas the solution had been difficult to isolate using a trial-and-error approach.

INTERACTIVE INVERSION

Interactive inversion allows the user to direct the parameter space search according to one's subjective judgment. To do so, the traditional numeric measure of data mismatch is replaced by the user's evaluation. Humans find it hard to express subjective judgment with absolute values; they generally find it much easier to compare different instances of the same process and rank them accordingly to certain criteria. Consequently, interactive inversion works by producing different possible solutions and presenting them to the user for evaluation and ranking. Genetic inversion (genetic algorithm, genetic programming, etc.) works by optimizing an ensemble of solutions, unlike other inverse strategies that search the solution space following a single path. Accordingly, they are an obvious choice for interactive inversion applications.

Here we describe the genetic algorithm used in the study, as well as the modification necessary to make it work interactively.

Genetic algorithm

Genetic algorithms (GAs) are a search method suitable for the global optimization of irregular multimodal functions. Starting with a set of initial solutions, these algorithms progressively modify the solution set by mimicking the evolutionary behavior of biological systems until an acceptable result is achieved. Because of their initially random and progressively more deterministic sampling of the function domain, they offer the possibility of locating the most promising areas of the solution space with relative efficiency. They are able to solve nonlinear, nonlocal optimization problems without the need for curvature information and, consequently, without the need for derivatives. This feature is particularly important for our application, since no derivative information for the subjective judgment is available.

The literature on GAs is extremely vast, and many subtle variations in the implementation of the basic concept underlying genetic search have been proposed. We refer the reader to Davis (1991) and Goldberg (1989) for a basic description of GAs and to Sen and Stoffa (1995) for some examples of applying GAs to geophysical problems. Here we briefly summarize the main features of the GA implementation we used; a more detailed description can be found in Boschetti et al. (1996).

In a GA a potential solution is represented in the form of a chromosome. Each parameter to be determined can be interpreted as a gene, and the concatenation of the parameters resembles the chain in a chromosome. Early GAs represented each gene in binary form, but further research (Davis, 1991; Wright, 1991) showed that a straightforward representation as real numbers can be more effective in high-dimensional spaces. Basically, a chromosome reduces to an array of real numbers in this implementation (the unknown parameters of the inverse problem). A GA works by applying three basic operators, corresponding to the biological processes of selection, crossover, and mutation, to a population (ensemble) of chromosomes.

Selection works by first assigning a measure of fitness to a chromosome, according to the value of the objective function (in numeric inversions) or subjective judgment (in interactive inversion) at the corresponding point in the parameter space. Then some criteria are applied to select the individuals used to generate the next generation of chromosomes. Among different criteria available in the literature, we chose linear normalization selection (Goldberg, 1989; Davis, 1991), in which a chromosome is ranked according to its fitness and is then allowed to generate a number of offspring proportional to its rank position. Using the rank position instead of the actual fitness value avoids problems that occur when fitness values are too close to each other (in which case no individual is favored) or too far from one another (in which case only one or two individuals only would be selected).

Once selection has been performed, new chromosomes are generated by crossover, i.e., by swapping genes among individuals, the number and location of the genes to be swapped being chosen randomly, in what is called uniform crossover

(Davis, 1991). Eventually, mutation is applied by randomly changing some genes at each generation.

Interactive GA

Formally, the modifications required for a GA to work interactively are minimal. Once a set of chromosomes is generated, it is fed to a forward code. Then a set of outputs (in the form of images of animations) is produced. The images (or animations) are visualized, and the user ranks them according to his subjective judgment. The ranking is input to the GA, which uses it to produce the next generation of chromosomes. Since ranking is used implicitly in linear normalization selection, effectively no formal algorithmic change in the code is imposed by replacing a measure of fitness with the subjective evaluation.

From an implementation point of view, some work needs to be done to make the subjective ranking input user friendly and to spare the user from tedious file editing. A user interface needs to be built that allows the user to view simultaneously all the different solutions generated by the GA, rank them easily, and proceed with the GA operations, possibly within a few mouse clicks. There is also an issue in avoiding human fatigue when examining numerous solutions for many generations; lack of attention and accuracy could result. These issues are dealt in the interactive inversion literature (Kishi and Takagi, 1999). Regarding our application, the description of the specific human interface is given as we lead the reader through the first experiment.

Some comments may be useful regarding the dimensionality and accuracy allowed by interactive inversion. To our knowledge, interactive inversion in real-world application has been attempted in problems ranging to a few tens of dimensions. In principle, no formal modification in the GA process is imposed by the interactive approach. Consequently, the same limitations valid for generic GA should apply here. We should consider, though, that ranking a large number of individuals becomes increasingly hard for a human operator; accordingly, small population sizes are recommended. Standard applications range between 10 and 20 individuals. Also, fatigue should be considered, so the run is often limited to a few tens of iterations. While in the GA literature there is no formal study on the relation between population size, number of function evaluations, and dimensionality of search space, problems of large dimension generally are tackled with larger populations. This may limit the applicability of this approach to very large problems. Should a user need to attempt an interactive inversion to large problems, some effort should be made to reduce the number of parameters to the minimum (a strategy that should be seriously considered but is often overlooked—for any style of inversion).

Particularly interesting is the effect of the subjective judgment on the accuracy of the inverse problem. In traditional inversions the shape of the search landscape is determined by the choice of cost function. This is fixed during the inversion and may or may not fit all the user's requirement; in geophysics, it rarely does. In an interactive inversion the human subjective judgment focuses directly on the desired features, implicitly shaping the search landscape according to the need of the inversion. This explains why results are often obtained with very few function evaluations. Also, the user may tune the search criteria during the inversion, depending on the knowledge accumulated during the process, providing another layer of interactivity to the approach.

Interactive inversion at work: Synthetic example

In this experiment we attempt to reconstruct the parameters (e.g., material properties) that produce a certain 2-D geological section as the result of an animation of thermal convection in the earth's mantle.

This kind of problem has implications for deep crust–mantle studies. A crucial parameter for understanding 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 metamorphosis and geochemical modification. The geotherm can be measured directly only in the shallowest few kilometers 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, viscosity of the mantle, and global partitioning of heat flow between oceans and continents).

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 modeling and a good deal of intuition based upon simple 1-D scaling laws. Such intuition can usually come from a user with high expertise in the field.

From the inversion point of view, this is a useful test problem for three main reasons. First, the fit to the geotherm for any given forward problem is quantitative so that, in principle, a genuine, traditional automatic inversion can be performed. Second, the practical limitations of the data can be simulated easily in the experiment. In the earth, 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. Third, the problem retains significant complexity, so that ambiguous solutions are possible and must be eliminated by recourse to estimates of geological likelihood based on experience and physical intuition. This is hard to code directly in a mathematical sense because we would need to consider such features as the shape of typical boundary-layer instabilities or the ways in which the flow patterns evolve over time—highly difficult to formulate in a pixel-by-pixel comparison of animations.

There is also the possibility that the additional information available in evolving the animation in two dimensions will allow an expert operator to speed up the inversion as well as discard models of little geological meaning. The extent to which these assumptions are helpful in constraining the inversion can be tested explicitly.

Experimental setup

The user is provided with a single image representing a 2-D geological vertical section (see Figure 1). 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. In particular, the parameters to be determined are the thicknesses and thermal diffusivities of two crustal layers, the viscosity of the underlying mantle layer, and the strengths of the radiogenic heat sources in each layer. This results in an eight-dimensional search space.

At the beginning the user is presented with ten animations (see Figure 2). This number was selected because ranking more animations becomes increasingly difficult for a human operator (normal GA runs usually involve a much larger population). Each animation has been generated by the GA through its standard stochastic behavior, coupled with the physical forward model. The user then views the animations 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, and (3) the user's general experience and knowledge of the area under analysis. The user interface has been build in such a way that each animation is viewed by clicking the mouse on a specific section (final frame). The final stages of each animation are viewed together to facilitate the ranking operation. The ranking is input by a mouse click in small windows underneath each animation. These may appear as minor details, but they are quite important in practical applications to prevent fatigue and focus the user on the problem by eliminating tedious manual operations. After the ranking is done, the GA starts its usual process and generates a new set of animations for the next evaluation. The process continues until the user is satisfied with the result, i.e., has an animation that looks geologically reasonable and produces a final result close to the target image.

Figure 3 is the result of the inversion at the third generation. Together with the ten new individuals, at the bottom we see the best individual from the previous generation. Keeping the best individual in a GA run is a standard operation; it provides

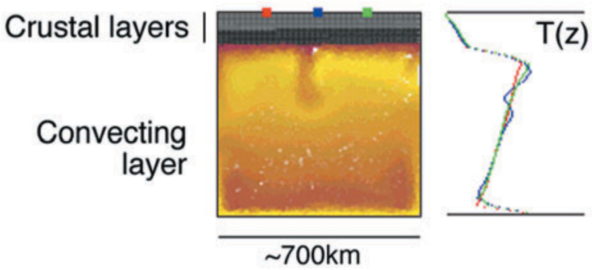

FIG. 1. Target section for the synthetic test. The section has been obtained using the same forward code as in the inversion. The model assumes upper-mantle convection underneath two crustal layers. In the inversion, the total thickness of the crust may vary, but the total depth of the system is assumed fixed.

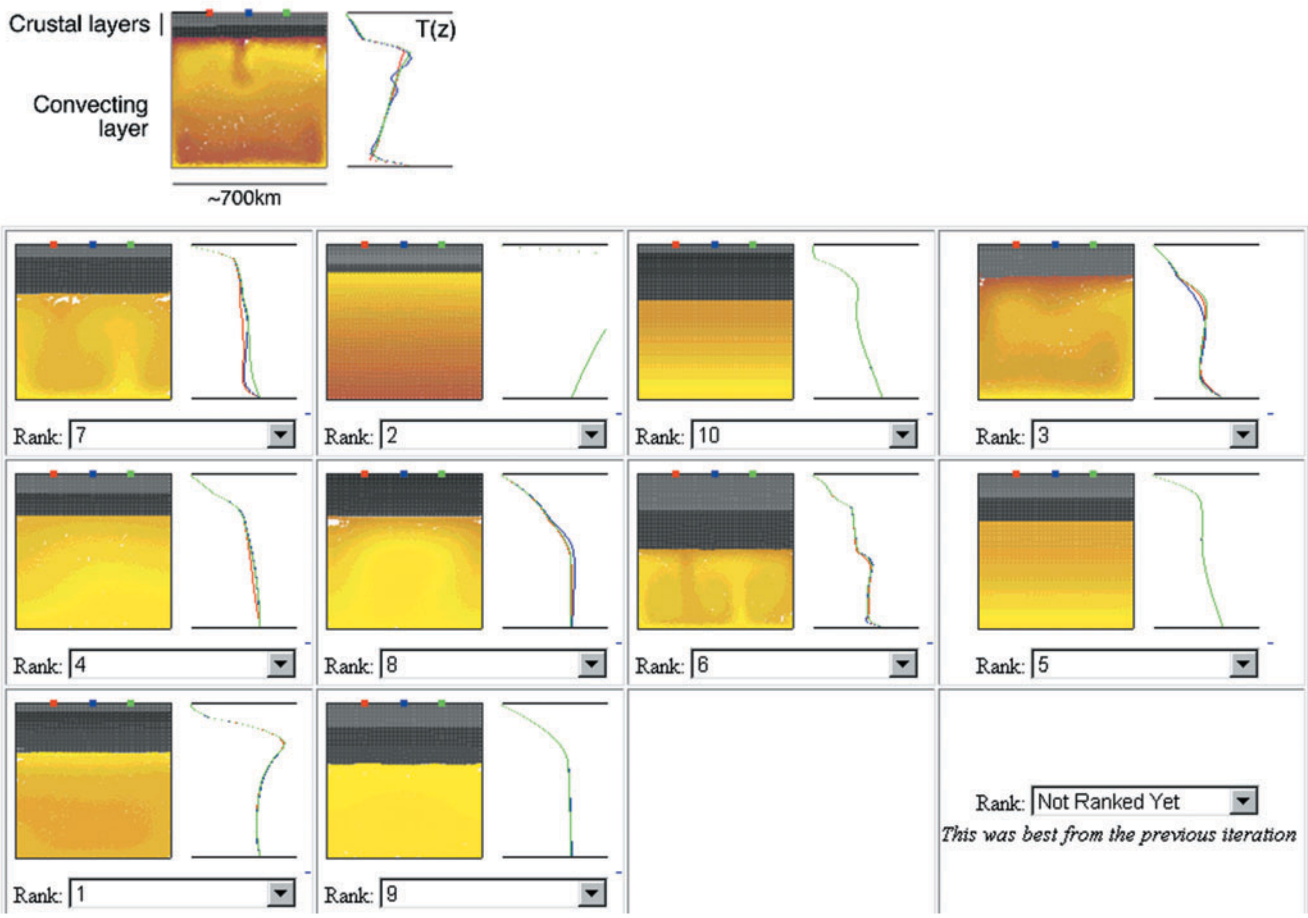

FIG. 2. First generation of the interactive GA run. The sections are the final stages of animations initialized randomly. At the top, the target image is reproduced.

a way to rank the new generation according to previous results. The kink in the mantle (dark hook), that is, the typical feature of the target image, starts to appear in the eighth individual. This animation is selected as the best individual.

Figure 4 shows the eighth and last generation. The choice to stop at the eighth generation was purely coincidental. In a real test we would have stopped as soon as a satisfactory match had been found. In this case we were interested in exploring the solution space and testing the GA behaviors. As we see, many solutions close to the target were found and show a good fit to the modeled geotherm.

The solutions also reproduce the structural features of the convection processes in the layer. These features are merely second-order signatures of the physics of the system. However, such small clues which hint at how a process was initiated are vital in geology, and it is reassuring to see that this information can be captured by the appropriate ranking choices.

The best results from the subjective inversion have eliminated one of the crustal layers. This highlights the fact that, for this simulation, some parameters produce first-order differences in the outcome, while others fine-tune the result. The total crustal thickness has a first-order effect, but it was parameterized as a sum of two internal layers whose relative thicknesses had a second-order effect on the simulation. In the GA, this is not an ideal situation because the relative thicknesses cannot be constrained. Parameters should be selected more carefully. The first pass of the inversion does, however, serve as a way to analyze the parameter space to help ensure the parameters are chosen to be as independent as possible.

A second test was run on the same model. This consisted of a traditional numeric optimization. The misfit used was the squared error between the target temperature profile and the one generated as the final result of the animation. The numeric inversion was run with exactly the same GA parameterization, number of individuals, and number of generations. The result from both the interactive and numeric inversion is seen in Figure 5. Both the quality of the result and the computation cost of the two inversions are comparable.

A number of interesting conclusions can be drawn from this experiment. First the similarity between the numeric and human-driven inversions is a very important result for geological applications, in which reliable data are rare and often sparse. For this specific application, 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 numeric inversion was given an unrealistic advantage

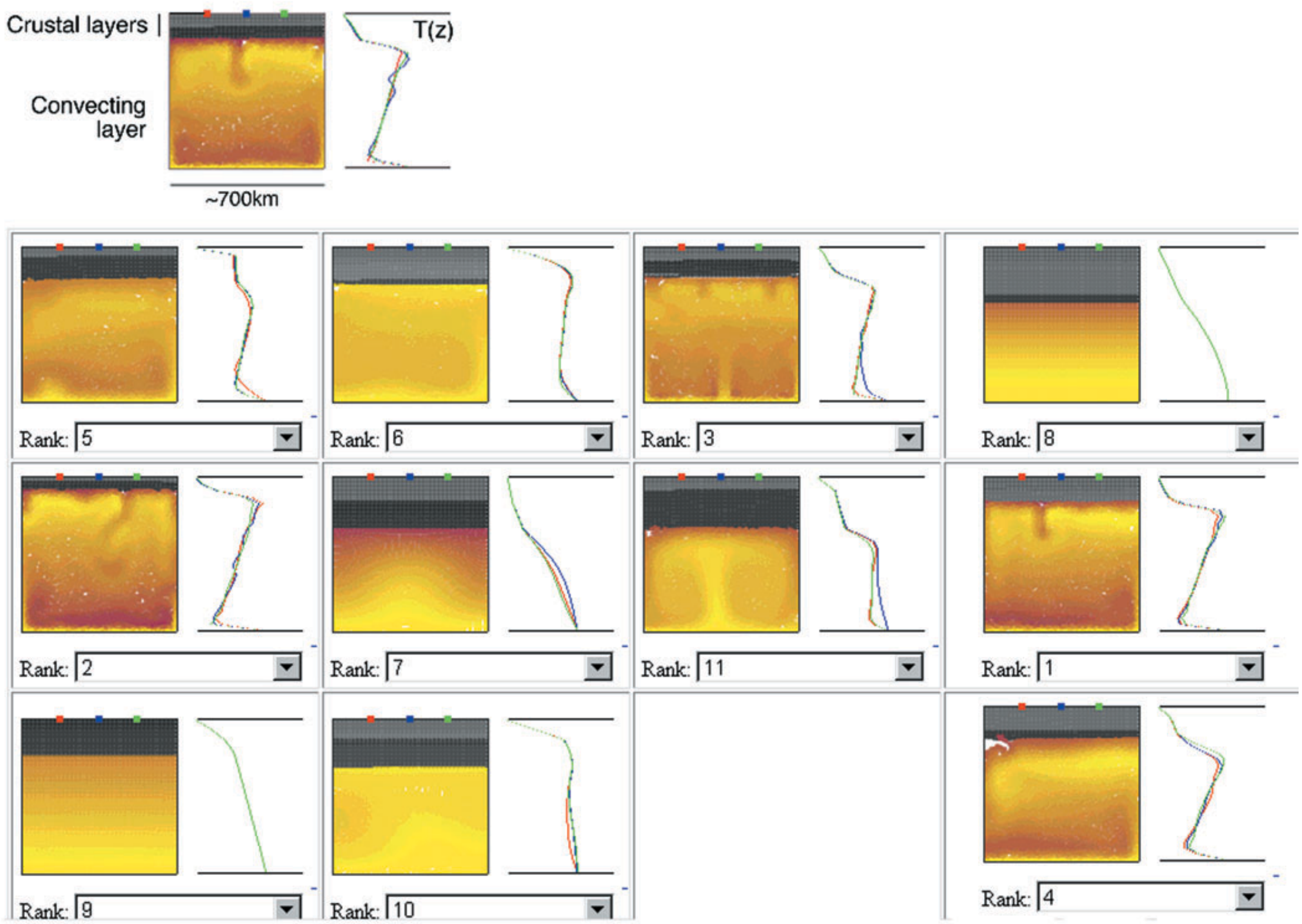

FIG. 3. Third generation of the interactive GA run. The eighth individual starts to show strong similarities to the target section. Notice also that the best individual from the previous generation (eleventh individual) is used in the ranking stage.

in assuming error-free temperature measurements along the entire profile. In real applications, reliable temperature data at depth would be rare, inaccurate, and at times absent. The ability of the geoscientist to direct the inversion to a successful solution without such data looks very promising.

Second, during the human-driven inversion, solutions characterized 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 used their knowledge and experience to select the crucial directions of the search. This process is completely impossible in a traditional GA run, in which only data misfit with no extra information is used.

Third, the geoscientist was also using his knowledge of the inner mechanics of GA inversion in his 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 last two strategies carry both advantages and disadvantages. The disadvantage lies in directing the GA run too much, with the risk of preventing its main feature, that is, the global search. The advantages are the possibility of speeding up the search and using a priori information. In this case there would be a double use of the information: first, in the subjective judgment, and second, in the ability to interfere with the standard GA run. Also, this provides the option of interactively controlling some GA parameters, such as population size and rate of mutation, depending on the convergence speed and variability in the population. This offers a completely new avenue to explore.

Finally, while numerical inversion is sensitive only to the temperature profile, human-driven inversion is particularly sensitive to geological structures and dynamic evolution. Both are modeled as color images in the animation. Specific choices of colors will allow the discrimination of certain features at the expenses of others. This confirms previous results on interactive inversions: the selection of a proper visualization and user interface becomes a crucial part of the inverse problem.

Experiment on realistic problem.

While the first experiment was a sort of proof of concept and helped us to understand the potential of this approach and to compare it to purely numeric inversion, here we present a case more relevant to geological/geophysical exploration modeling.

This experiment was conducted to verify the usefulness of the technique in the real working environment of geodynamic modelers. A numeric model was being developed to test whether a particular interpretation of a geological cross-section was mechanically self-consistent. The model to be run required

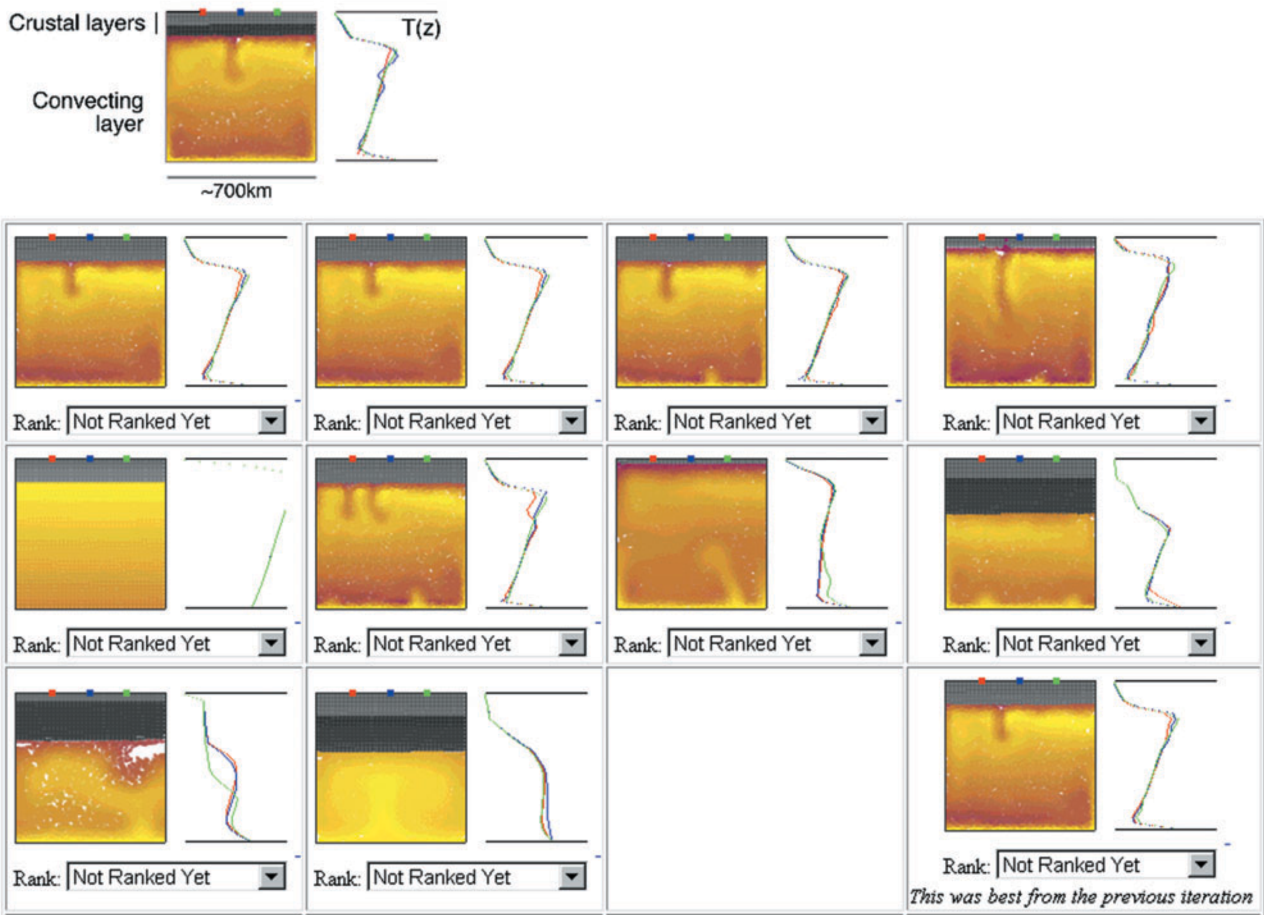

FIG. 4. Last generation (eight) of the interactive GA run. Many individuals now show similarities to the target section.

reactivating a sequence of three existing extensional basins during a compression phase of deformation. The difficult part of this computation was to obtain a mechanically self-consistent initial condition for the reactivation (i.e., the three extensional faults). Trial-and-error modeling of an extended, layered system found a suitable starting point after numerous iterations which took 90% of the time for the entire modeling exercise (in this case, two weeks).

It was interesting to test whether the interactive inversion could produce the desired initial condition more rapidly than the trial-and-error approach. A rough sketch of the desired result was given to an operator who had not participated in the trial-and-error exercise, along with a suitable model with a number of free parameters.

The pattern seen in the field is summarized in Figure 6. The main feature of the section is the three extensional faults with approximately regular spacing. The aim of the analysis is to deduce what kind of stress and material properties can allow the formation of such a faulting pattern. To reduce user bias about the proper layer thicknesses, the colors of all the materials were set to black, with brittle structures shown in red.

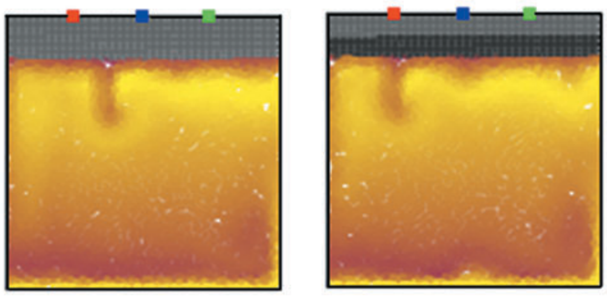

FIG. 5. Best result from the interactive inversion (left) and the numeric inversion (right).

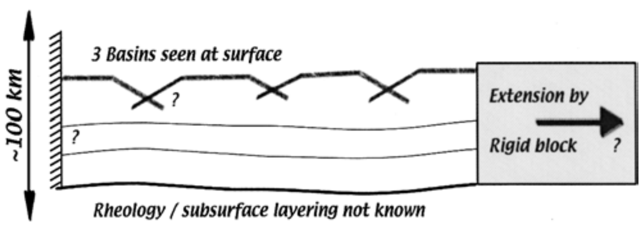

FIG. 6. A sketch of a geological section, containing the three extensional faults as seen in the field. This was the target for the real-case experiment.

Figure 7 shows the best model generated by the trial-and-error process. Figure 8 shows the solution found at the first attempt with the interactive inversion. The three-fault pattern has been reconstructed successfully. The interactive inversion needed eight GA generations to find the target section, requiring a few minutes of human time to rank the generations and 2 hours of computer time to produce the animations for each generation. The computer time could be reduced greatly by implementing the procedure in parallel (each model is entirely independent of the other, so this operation is relatively trivial).

There is an additional benefit to the interactive inversion: the process of selecting the best model also maps out much of the local parameter space. Post analysis of the parameters for the better models reveals which are important for the desired behavior and which are not. Further, since the GA provides models closely related to the best one, the influence of the controlling parameters on the outcome can be discerned (i.e., within the subjective context, we are obtaining information about the local derivatives).

Figure 9 shows the ten sections of the last GA iteration. Model G is most like the cartoon. From the exact placement of the brittle structures, this is the only useful model; however, geologically similar results C and D also have nearly periodic brittle structures in the uppermost layer. Analysis of the parameters for these models shows that models C, D, and G are identical except for the upper layer thickness; clearly, the spacing of the brittle structures is controlled most strongly by this parameter. We learn, therefore, not just how to produce a particular model but also the controlling physical variables we can use in related models.

DISCUSSION

We have presented two quite different applications, but a few more words should be added on the technique itself.

The main feature of the method is that it offers a way to include prior geological knowledge and experience into the inverse process. This is extremely hard to achieve in a rigorous mathematical formalism. As mentioned above, traditional inverse techniques include prior constraints which can

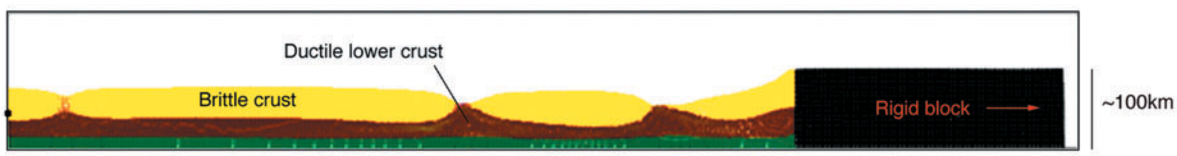

FIG. 7. Result of the manual forward modeling to reconstruct the sketched section in Figure 6.

FIG. 8. Result of the interactive inversion on the real fault pattern.

be specified easily in purely mathematical terms—for example, imposing smoothness or sharp boundaries, or simplified geological shapes. These assumptions are generated from mathematical convenience in the first instance and geological relevance in the second. As a result, they rarely allow proper modeling of the complex geology. Alternative approaches have been attempted where the complexity of geological structures is captured by statistical means (see, for example, Torres-Verdin et al., 1999), but such techniques are useful only where exhaustive geological data are available.

This is largely at the core of the difficulty in communication often experienced between geophysicists and geologists which results in a lack of common ground between the two camps. Geologists may perceive geophysicists as being lost in an abstraction far removed from real geology; geophysicists often see geologists as hopelessly resistant to mathematical rigor.

The technique we have developed tries to build a bridge between the two views—by providing an obvious and simple way to include geological knowledge into the inversion with no need for complex mathematical modeling. It allows the user to watch the inversion as it proceeds through the parameter space and so removes much of the black-box nature of the automatic inversion. The insights that may be obtained from seeing the progress of the inversion as it runs range from a better understanding of the parameter space to a better understanding of the range of variability of geological processes. This is very important since often experience and strong preconceptions may hinder possible alternative geological interpretations. The stochastic sampling of the solution space typical of GAs may develop unexpected solutions able to suggest alternative geological scenarios not considered before. In a typical automatic, black-box inverse run, such alternative solutions would be most likely discarded and lost. This method offers an opportunity for brainstorming between inversion and user. Such brainstorming could go one step further because there is no reason to limit the subjective judgment to a single user. More users could rank the solutions, and the final ranking could be obtained as a combination of the individual ones. Different geologists might work on the same inversion; even better, geologists and geophysicists could cooperate in the inversion, providing two different classes of knowledge and experience to the problem.

While the interactive approach is a necessity for processes where only a subjective ranking exists, the methodology may also be of use in traditional inversions where ambiguities are present (e.g., inverting potential field data to determine buried structures). In this case, the judgment of the experienced user

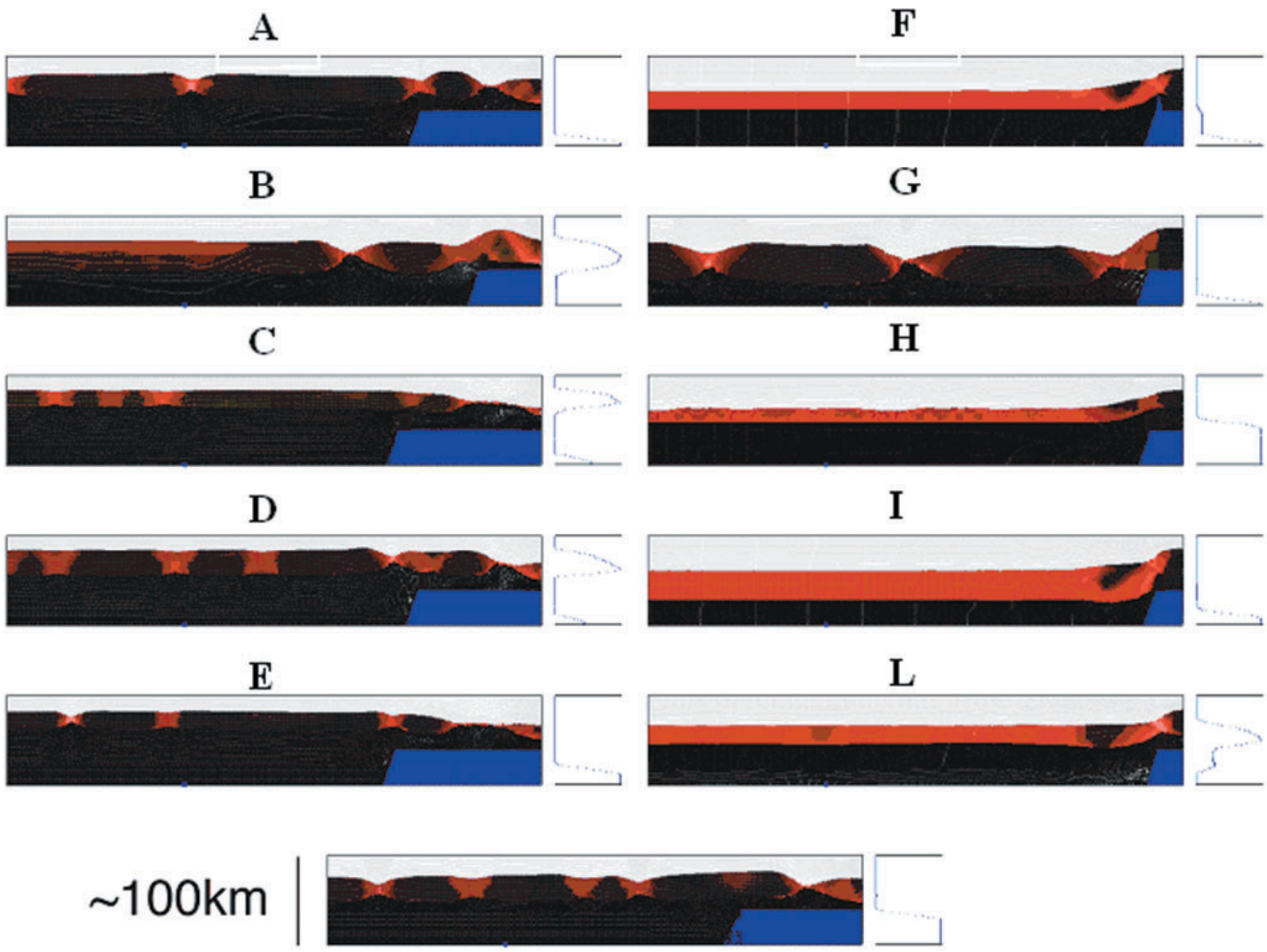

FIG. 9. Final generation of the interactive GA for the real test.

is required to discriminate between models which have the same objective fit to the data but which might be quite distinct in terms of geological probability. Thus, the numerical mismatch would guarantee data fitting, and the subjective judgment would disregard ungeological scenarios.

The use of the GA also provides the ability to explore the parameter space of the problem in various ways for both the traditional inversion and the interactive approach. We discussed how the final ranked set of models produces a sensitivity study in the parameter space surrounding the preferred model. Earlier in the inversion process, the parameter space is sampled more broadly. This allows us to extract some further information about the system we have chosen to model. For example, "How likely is a given scenario?" An analysis of the size of the region in parameter space where models are (subjectively) similar gives an indication of whether the preferred model is produced by a rare combination of parameters unlikely to be found in nature. One might also ask, "How many different classes of behavior are possible for a given model?" The answer here is again subjective because it relies on the classification skills (and preferences) of the user, but it is nonetheless instructive. On a similar note, given two different behaviours of a system, what are the significant parameter changes that differentiate the two? Clearly, a directed inversion does not provide the necessary sampling of the parameter space to answer such questions definitively, but the fact that the user is exposed to a range of different models at least raises this possibility.

We saw that the proper design of the experiment also becomes significant in achieving an effective result. As is true in general for any kind of inversion, the parameterization should be chosen in such a way that the physical properties we attempt to reconstruct are as orthogonal to one another as possible. For interactive inversion, however, other factors become relevant, such as the manner in which the information is presented to emphasize the importance of one parameter over another. This is not something that the average expert in inverse methods is familiar with and suggests the need to involve human-interface specialists in the practical implementation of this algorithm.

CONCLUSIONS

In geosciences, measurements rarely supply sufficient constraints on a problem to allow for a unique and stable solution from inversion. Additional external constraints are used in these cases but are often constructed more for mathematical convenience than for strict geological appropriateness. This is because it is often hard to code analytically or numerically geological a priori information. We have presented a simple way in which an inverse run can be driven entirely by subjective judgment from users with reasonable geological knowledge and experience. While this approach does not remove nonuniqueness from the solution, it allows for the reconstruction of solutions satisfying basic criteria of geological reliability. The method has proven to be successful in both a synthetic and a real application, and it compared well to traditional numerical approaches. It requires only minimal time and effort from the user; most computational time has been absorbed by computer forward modeling (as in any inverse application). We believe this technique can greatly widen the range of geological problems admissible for inversion and can be used for many applications in geosciences, either alone or in conjunction with traditional numeric techniques.

REFERENCES

Boschetti, F., Dentith, M., and List, R., 1996, Inversion of seismic refraction data using genetic algorithms: Geophysics, **61**, 1715–1727.

Davis, L., 1991, Handbook on genetic algorithms: Van Nostrand Reinhold, New York.

Goldberg, D. E., 1989, Genetic algorithms in search, optimization, and machine learning: Addison-Wesley Publ. Co., Inc.

Kishi, K., and Takagi, H., 1999, Developing montage systems for study on interactive evolutionary computation: SOFT 3rd Workshop on Evaluation of Heart and Mind, 15–18.

Sen, M. K., and Stoffa, P. L., 1995, Global optimization methods in geophysical inversion: Elsevier Publ. Co.

Takagi, H., 1998a, Intercative evolutionary computation: System optimization based on human selective evaluation: Internat. Conf. on Intell. Engin. Systems, Inst. Electr. Electron. Eng., 1–6.

Takagi, H., 1998b, Interactive evolutionary computation—Cooperation of computational intelligence and human KANSEI: 5th Internat. Conf. on Soft Computing, 41–50.

Torres-Verdin, C., Merletti, G., Victoria, M., Pedrel, J., and van Riel, P., 1999, Geostatistical inversion and lithology discrimination: Honoring 3D seismic data and well logs to delineate sands thinner than tuning resolution: Geoinversion Summer Workshop, Soc. Expl. Geophys.

Wright, A. H., 1991, Genetic algorithms for real parameter optimization: Presented at the Foundation of Genetic Algorithms.