Bringing conceptual geological models to life

Chris Wijns[1,*], Louis Moresi[1], Fabio Boschetti[1], Alison Ord[1],
Peter Sorjonen-Ward[1], and Brett Davies[2]

[1] CSIRO Exploration and Mining, PO Box 437, Nedlands, WA 6009, Australia
(email: chris@ned.dem.csiro.au, Fax: +61 8 9389 1906)
[2] Normandy Mining Ltd., PO Box 1143, West Perth, WA 6872, Australia
* *now at* Dept. of Geology and Geophysics, University of Western Australia, Crawley, WA 6009, Australia

Abstract

We present a first step towards the development of a system that would allow geological models to evolve backwards in time. The method provides for the inclusion of geological knowledge and expertise in a rigorous mathematical inversion scheme, by simply asking an expert user to evaluate different geological models visually. The potential of the technique is demonstrated for a number of conceptual geological models.

Introduction

In recent years fast computers have led to the development of quite sophisticated forward modelling of geological processes. We can answer questions such as “What faults or fractures will be generated by this stress field in this material?”, using accurate modelling of material behaviour. However, we really would like to solve the inverse problem, which is based upon field observations, *i.e.* “What stress field or material behaviour can generate these faults?”. Our task is thus to invert present-day observations in order to unravel the time evolution of a geological formation.
The first approach used by geologists is to construct time-dependant conceptual models in order to explain geological evolution. This is a human method of inversion which is based upon an expert’s knowledge and experience, but it is highly visual and usually offers little hard data. In our quest to ground such conceptual models in the laws of physics, we need to find the correct combination of initial conditions and material parameters in order to reproduce and thus validate the geologist’s visual model. We lack numerical targets for mathematical inversion techniques, and so we have chosen a method of visual image ranking as a means for exploring geological parameter space. This approach capitalises upon the inherent subjectivity in geology.

Method

We have applied a method called interactive evolutionary computation (IEC) to geological problems in which subjective judgment is necessary to evaluate geological models in the absence of sufficient constraints. The process works by producing different possible solutions from a numerical forward model and then presenting them to the user for judgment and ranking. The ranking directs the choice of parameters for the next round of forward models, and this process continues in an iterative manner. We believe that the system represents an advance on traditional, time-consuming trial and error approaches by providing a formal role for relevant geological experience and knowledge in inversion. The traditional numerical measure of data mismatch is replaced by the user’s subjective evaluation.
Our IEC system works by linking a geological forward model to a genetic algorithm (GA). Boschetti et al. (1996) [1] present a more detailed description of the specific GA implementation used in this work. The forward modelling code used here is a particle-in-cell finite element code. Details of this code can be found in Moresi and Solomatov (1995) [2] as well as on the World Wide Web at http://www.ned.dem.csiro.au/research/solidMech/PIC/Ellipsis.htm.

Models

The example included here seeks to reproduce common extensional structures in a rifting environment. The ranking of forward model results is based upon comparison with a target image, in this case the simplified line sketch of Figure 1a. Although the forward models evolve in time, in this introduction to our inversion method, only the final configurations are used for visual evaluation. The model is composed of two initially homogeneous crustal layers, on top of which is a low density, low viscosity background material which does not interfere with the mechanics of the problem. This initial configuration is illustrated in Figure 1b. The upper layer has strain-softening properties, which cause initial strain perturbations to localise. This yield law prescribes an upper limit σ_y on the stress according to the power law

$$\sigma_y = \begin{cases} (B_o + B_p p)\, f(\varepsilon) & p > -B_c \\ 0.001\sigma_y & p < -B_c \end{cases}$$
$$f(\varepsilon) = 1 - (1 - E_a)\,(\varepsilon/\varepsilon_o)^2 \tag{1}$$

where p is the pressure, ε is the accumulated plastic strain, and the remaining coefficients are arbitrary. Eight forward models are run at each step of the inversion, and we vary six upper crustal strength parameters: viscosity and five yield law coefficients.

Extension proceeds by applying a uniform velocity to the right-hand boundary. Figure 1 illustrates the evolution of results using the IEC algorithm. In our continuum forward-modelling code we infer that bands of high localised strain represent faults. Accumulated strain is indicated by areas of darkened material, and the degree of shading is indicative of the amount of strain. The first panel (i) contains no models which resemble the target image. In fact, only two models have converged numerically and been extended to full length. Models 6 and 8 exhibit structures penetrating the upper layer, and for this reason they are ranked first and second, respectively. The other models do not merit ranking, but are nonetheless weighted randomly by the GA in order to fill up the remaining six positions.

Panel ii contains the second iteration of the algorithm. Once again there are four models which do not converge numerically, but those that do converge generally display more crustal-scale structures than in the first iteration. The rank of each model result is noted below each image. We continue iterating in this manner a total of six times, at which point half of the resulting images are qualitatively similar to the target image (panel iii), and the process is halted. The outcome is a set of crustal strength parameters that leads to the behaviour observed and inferred in the field. These (dimensionless) parameters are listed in Table 1, together with their initial ranges, the final values which give rise to the highest-ranked model of the final generation (Figure 1,panel iii, third model), and the range of the parameters for the four top-ranked models of the final generation.

Parameter	Initial range	“Best” value	Range
Viscosity	5000 - 10000	9000	9000
Cohesion B_o	0 - 2000	0	0
Pressure dependence B_p	0 - 1.0	0.2	0.2
Tension limit B_c	10 - 1000	100	100 - 200
E_a	0.1 - 0.9	0.2	0.2
ε_o	0.1 - 1.0	0.7	0.3 - 0.7

Table 1: Six upper crustal layer parameters are free to vary during the inversion. The “best” values give rise to the top-ranked model of the last generation. The last column gives the range of parameter values for the top four models of the last generation.

Conclusions

For the above problem, arriving at a suitable combination of parameters would previously have involved one of two more laborious approaches: the manual selection of parameters by trial and error, or an exhaustive coverage of all parametric space. Trial and error may succeed with a limited number of parameters, but depends upon the user’s knowledge of the coupling and feedback between parameters, which, in highly non-linear problems involving complex crustal rheologies, may be impossible. A parametric study quickly becomes unfeasible due to the sheer number of models which must be run as the number of parameters is increased. Neither of these approaches takes full advantage of the expert knowledge of an experienced geologist.

The technique of IEC has considerably diminished the effort required to explore parameter space during the inversion of conceptual models in geology. We bypass the lack of numerical data for an inversion target by using a GA together with image ranking to focus on a visual target. This approach exploits the experience and knowledge of an expert user in a visual and therefore intuitive environment.

References

[1] F.Boschetti, M. Dentith, and R. List, Inversion of Seismic Refraction Data Using Genetic Algorithms, Geophysics, pp. 1715-1727, 1996.

[2] L.-N. Moresi and V.S. Solomatov, Numerical Investigation of 2D Convection with Extremely Large Viscosity Variations, Physics of Fluids, vol. 7, no. 9, pp. 155-164, 1995.

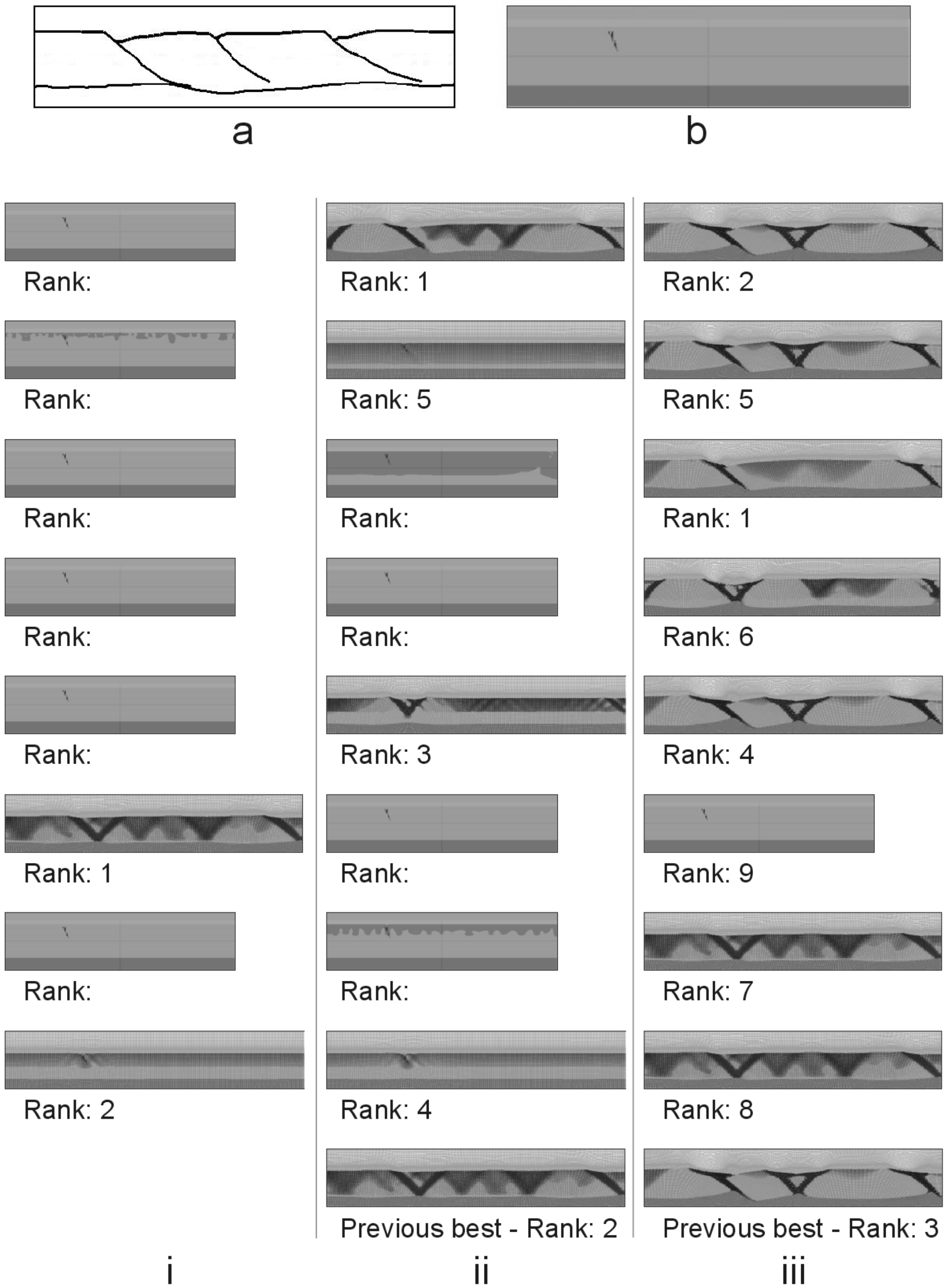

Figure 1: Target image (a), initial geometry of the crust (b), and evolution of the IEC inversion. Panels (i) to (iii) represent the first two and the last generation of the GA. Images are ranked according to their similarity with the target image. Some models have not been extended to full length because of numerical non-convergence. These are left unranked, and the GA orders them randomly so as to fill up the bottom rankings.